The Determinants, Implications and Interaction of Consumer Sentiment

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The Determinants, Implications and Interaction of Consumer Confidence: International Evidence

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Abstract

According to Behavioural Economics, consumer expenditures depend on not only their financial conditions but also their attitudes, and the latter is reflected in consumer sentiment (or confidence). In 1946, Katona developed the Index of Consumer Sentiment to quantify sentiment measure through survey data. Since then, sentiment has received constant media attention and been studied by a long and rich string of literature. However, researchers and analysts have yet to reach a consensus on its determinants and implications. Moreover, although sentiment surveys are regularly conducted in many countries nowadays, the important issue of sentiment's cross-country interaction is largely ignored in literature.

Nonetheless, one thing that existing studies seem to agree on is that sentiment plays an especially important role during economic turning points. As a result, the 2008 Global Financial Crisis has brought the relationship between sentiment and macroeconomic conditions back to the forefront. While it remains difficult to assert whether the collapse of confidence was the cause or the consequence of the crisis, most academics and policy makers agree that the erosion of confidence has ensured the depth and longevity of the crisis regarded by many economists as the worst financial crisis since the Great Depression. Motivated by the global panic and fears since the Global Financial Crisis, and the new and important role sentiment may have played in triggering and prolonging the economic downturn, our study seeks to address the following three interrelated issues: *determinants*, the underlying forces behind the erosion of confidence; *implications*, its impacts on the real economy; and *interaction*, the channels in which the sentiment shocks transmit across international markets.

We focus on the role of Economic Policy Uncertainty when we study the deter-

minants of consumer confidence. By doing a thorough data analyses with a VAR (vector autoregressive) model, including performing Granger Causality Test, running Impulse Response test and studying Variance Decomposition results, we confirm the usefulness of economic policy uncertainty, and also discuss its implications - consumer confidence, or sentiment, may be a measure of uncertainty.

We then move to international data on consumer confidence, and study its transmissions. We generated the spillover index, which is based on forecast error variance decompositions from VAR models. We are able to discuss the direction of relationships among consumer sentiment in different countries. Not surprisingly, we have found that the consumer sentiment in the US plays a central role.

Finally, we study the implications of consumer confidence, focusing on its role on house price changes. Again, we use a VAR model to study the dynamics of consumer sentiment and house price. We find that consumer sentiment is very powerful in explaining the percentage change in house price. Then we study and compare consumer sentiment within different income tiers, age groups, and regions. We find that the sentiment by mid-aged people, people with higher income, and people who live in certain regions, has the biggest explanatory power on house price change. it seems that the sentiment of people with better knowledge and experience in housing market was more valuable in predicting house price change. This leads us to wonder: in addition to consumer sentiment, by adding sentiment by professionals who work in the housing market, we might be able to find a better sentiment proxy that could have better explanatory power on house price change.

Therefore, we proposed a two-step approach to achieve this goal. The first step was to construct a better consumer sentiment index, that is housing specific. We looked into the survey questions by University of Michigan's Survey of Consumers, and started with the questions that better represent peoples' sentiment on housing market. We then did a Stepwise Regression to select the set of variables that were able to explain the most variance on house price. Afterwards, we finalised our choice of questions by pairwise Granger Causality test results. We used the responses of these questions to construct a housing specific consumer sentiment.

Our second step was to construct a sentiment of people who are the centre in the housing market. We aim at providing a sentiment measure that combines consumer sentiment (using the housing specific one we constructed), builder sentiment, realtor sentiment, and lender sentiment. Principal Component Analysis is used for the construction of the sentiment measure. And the measure turns out to be very successful in explaining house price change, compared with other sentiment measures.

In summary, we provide a thorough study on consumer sentiment and have some interesting results. Our findings should be valuable for both researchers and practitioners.

June 22, 2020

Declaration

The work in this thesis is based on research carried out at the the Business School, Durham University, England. No part of this thesis has been submitted elsewhere for any other degree or qualification and it is all my own work unless referenced to the contrary in the text.

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Doing the PhD is an extremely difficult challenge for me. It can not be done without any of you. Thank you all from the bottom of my heart.

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Chapter 1

introduction

The recent 2008 Global Financial Crisis is regarded by many economists as the worst financial crisis since the Great Depression (Pendery, 2009). Researchers and professionals have tried their best to untangle the underlining mechanisms behind this severe and prolonged economic downturn, and identify the important lessons that one should learn. Among these findings, most academics and policy makers agree the erosion of confidence has ensured the depth and longevity of the crisis (See, for example, Petev et al. (2011)). The problem of the role consumer confidence plays in economy has been bought back to the forefront.

Consumer confidence (which is often referred to as consumer sentiment, and these two terms will be used interchangeably throughout this thesis) captures the difference in consumer attitudes when making buying decisions, while her financial condition and the surrounding business environment stay the same. Classical finance theory assumes rationality of the consumers (Friedman, 1957). In other words, it disregards the role consumer attitudes play, with the assumption that the differences in individual attitudes would cancel out. However, the theory fails to explain many economic phenomena, such as depressions (Colander et al., 2009). In Keynes (1936)'s revolutionary work that explained the causes of the Great Depression, he proposed the idea of "animal spirits", suggesting that the change in consumer taste may influence investment. In line with this notion, Katona (1953) proposed the theory of psychological economics, and suggested that expenditures could depend on both the "ability to buy" and the "willingness to buy". While the former is an objective factor about the consumer's financial condition, the latter captures the subjective aspect about the consumer's attitude.

Since the proposal of the concept of consumer confidence and the development of its proxies, consumer confidence has been studied by a long and rich string of literature and received constant media attention for more than 50 years. However, researchers and analysts have yet to reach an consensus on many issues related to consumer confidence, such as its usefulness in explaining economic phenomena, its predictory power on future expenditure, its determinants and implications, and the underlying mechanism. In this thesis, we will revisit and try to untangle these important issues, by applying new research methods, using new data, and including new variables.

In the next chapter (Chapter 2), we will focus on the following research question: what drives the changes in consumer confidence? In Katona (1972)'s opinion, consumer confidence is a unique and complex variable constantly influenced by a large range of variables, unique events, mass media, etc. For example, big events such as the 1990 Iraq War and the 2001 September 11 attacks were believed to have a large impact on consumer confidence. And these factors can only be identified afterwards. Similarly, Mueller (1963) summarised the reasons why data on consumer attitude are needed: firstly, it combines many economic factors, therefore, measuring it directly is easier and more reliable. Moreover, it is not merely a reflection of financial development. For example, it can be influenced by news, and therefore, same stimulus may be perceived differently. Finally, it shows the impact of political or economic events. Obviously, Katona and Mueller are implying that it may be impossible to study the determinants of consumer confidence since they are too many to list (with some of them nonquantitative) and too unique to study (with some of them unable to be known beforehand).

However, we can still make several observations from their discussions. Firstly, consumer confidence is probably not a subjective factor after all, but instead, it is driven by information. In other words, the rational assumption of consumers still holds. Consumer confidence is not "animal spirit" which captures short-term human emotions, but an implication of the impact of all the subtle information (including information on economy, news, political events, etc) on consumers that are relative to their buying decisions. Or in short, determinants of consumer confidence do exist. This view is supported by an empirical study by Barsky and Sims (2012).

Secondly, after carefully reading their works, we can easily identify a few variables that are good candidates as the potential determinants of consumer confidence, such as unemployment rate, stock market index, interest rate, etc. For example, in the essay “Theory of Expectations”, Katona (1972) stated that “income or price expectations may be influenced by taxes, interest rates, ..., etc.”

But thirdly, Katona and Mueller believe that these few macroeconomic and financial variables are unlikely to determine consumer confidence constantly well. This has been verified in literature. Since the change in consumer confidence precedes the change in economic and financial variables, how can we expect the latter to explain the former well all the time?

These three observations imply that if we find a leading variable that also contains information related to consumers' buying decisions, it may be a good candidate as the determinant of consumer confidence. Motivated by this idea, in this chapter, we propose *economic policy uncertainty* as a potential determinant of consumer confidence.

In particular, the reasons that we choose economic policy uncertainty as our main variable are as follows. Firstly, economic policy uncertainty contributes to people's expectation about government policy. And the expectation about government policy is one important kind of expectation that may have a substantial impact on consumer confidence, because it affects not only personal income expectations, but also their economic outlook (Katona, 1972). Secondly, economic policy uncertainty may reflect information on many aspects, such as political events, terrorist attacks, and news, which are related to consumer confidence but not covered by other so called “objective” economic variables. Moreover, it may play an extremely important role in times of crises and recessions. Unlike the commonly considered economic variables, economic policy uncertainty is a leading indicator that implies the lack of confidence of the government. Thirdly and most importantly, we suggest that economic policy uncertainty is linked with consumer confidence through a special channel: economic policy uncertainty leads to consumer uncertainty, and higher consumer uncertainty implies lower consumer confidence.

Motivated by the theoretical evidence we discussed and aligned with intuition, we have the following hypothesis: higher economic policy uncertainty leads to lower consumer confidence. Through VAR models and thorough analyses of the US and European data, we study whether and to what extent economic policy uncertainty affects consumer confidence, controlling for other economic variables; and what the underlying mechanisms that drive the relationship between economic policy uncertainty and consumer confidence are.

The results in Chapter 2 clearly show that although the majority part of consumer confidence can be explained by economic policy uncertainty as well as other more "objective" economic and financial variables, there is always a part that remains unexplained. What is more, the unexplained part is much larger at business turning points. This implies that consumer confidence contains essential and unique information, which is not captured by other variables.

While the model we built was quite solid and robust, and in line with previous research on this area, there is one possible determinant of consumer confidence that was left out of the equation intentionally: the consumer confidence in other countries. From the figures and discussions in the previous chapter, we can clearly observe similar trends for consumer confidence in different countries. They all reached their troughs during the Global Financial Crises, and reached their peaks at similar periods as well. This leads us to wonder: how does the consumer confidence in one country affects that in another country? What can the transmission of consumer confidence tell us? In Chapter 3, we aim at answering these questions. In other words, instead of focusing on the relationship between other variables and consumer confidence, in this chapter, we focus on the consumer confidence in different countries and regions.

We believe the international transmission in consumer confidence exists for several reasons. First, it is due to the global financial interdependence, which has been widely studied and proven (Cooper, 1985; Longin and Solnik, 1995; Corsetti et al., 2005), and also due to the contagion and co-movements in financial markets, which also attracts research interests (Pericoli and Sbracia, 2003; Ahmad et al., 2013). Intuitively, the interdependence and contagion of the financial market may lead to the interdependence and contagion of consumer confidence among different countries.

Secondly, news has an impact on global financial market (e.g., Albuquerque and Vega (2009); Apergis (2015)). In Chapter 1, we discussed the interpretations of consumer sentiment, and suggests that it contains information such as news that is not included in other financial variables. A property of news is that it spreads over country borders quickly. Therefore, it provides a good channel for the transmission of consumer sentiment.

Thirdly, there are also social psychological reasons for the transmission of consumer confidence. There is rich evidence for "herd behaviour" of investors in behavioural finance literature (Scharfstein and Stein, 1990). This implies that under certain circumstances, investors simply mimic the investment decisions of others. We can easily extend this idea to general consumers. It is reasonable to suspect that when consumers form their attitude on the willingness to buy (which is measured by consumer confidence), they sometimes simply mimic other people's attitudes.

In summary, based on the existing literature in the interdependence of financial markets, the contagion in financial markets, news effects on financial markets, and herding behaviour in social psychology, we suggest that the consumer confidence in one country is affected by that in another country. The level of co-movement and spillover is affected by economic, political and geographic factors. In particular, when consumer confidence changes dramatically in one country (especially a leading one), consumer confidence in other countries may follow the same trend.

As mentioned in the previous chapter, consumer confidence is a leading variable. By the discussion here, the large spillover of consumer confidence may even lead the change in consumer confidence in the majority of countries. Therefore, it may have some predictory power, too. Large spillover of consumer confidence has predictive power for economy.

Following the approach in Diebold and Yilmaz (2012), we generate the spillover indices among G6 countries, which is based on forecast error variance decompositions from VAR models. We are able to discuss the direction of relationships among consumer sentiment in different countries. Not surprisingly, we have found that the consumer sentiment in the US plays a central roles. We also use a VAR model to study the relationship between total spillover and economic activity, and confirms its leading role in predicting the latter.

In Chapter 2, we study the determinants of consumer sentiment, focusing on the role of a new variable, Economic Policy Uncertainty. In Chapter 3, we study its interactions among different countries. From the results, we find that the economic variables can explain part of consumer sentiment, and our new variables have extra explanatory powers. Nonetheless, there is part of consumer sentiment that is left to be unexplained by other variables. This implies the consumer sentiment may have unique information in itself, and it may have unique explanatory power on other economic variables that may interest us. Hence, in Chapter 4, we study the effects of consumer sentiment on other variables, or specifically, on house price. With better understanding of the underlying mechanism of consumer confidence that we find in Chapters 2 and 3, we may be able to provide a thorough study on sentiment's role on house price.

There is wide literature on the effects of consumer sentiment. Some focus on how consumer confidence affects expenditure of durable goods. Most researchers agree that consumer sentiment do have some unique information that helps predict future expenditure. And on the other hand, some focus on the relationship between sentiment and stock market performance. The general finding is that investment sentiment affects the investment.

However, There is limited evidence on the effects of consumer sentiment on house price, possibly because of the unique characteristics of house purchase. It can be regarded as both a durables/services consumption, as well as an investment. Therefore, the relationship between consumer sentiment and house price becomes more ambiguous and complicated, and is worth studying.

Researchers have been interested in finding the determinants of house price for a long time. Apparently, the level of demand and supply determines price. Housing market is not an exemption. House price is determined by the demand and supply factors. Higher demand and lower supply lead to higher house price. Following this idea, researchers have confirmed that the housing market is influenced by the state of the economy, interest rates, real income and changes in the size of the population, etc.

In addition to these economic factors, people also agree that sentiment plays a role in house price change. But what role it plays depends on how to interpret it. Based on Ludvigson (2004), one economic interpretation is that it captures reduced uncertainty about future, and therefore diminishes precautionary savings motives. As a result, consumer will save less, and consumption growth will be lower in the future. If it is the case, consumer sentiment might be negatively related to house price. However, this interpretation is rejected by the economic evidence.

The second interpretation proposed by Ludvigson (2004) is that consumer sentiment captures the expectations of future income. It is founded on the rational expectations – permanent income hypothesis (REPIH). If consumer sentiment higher, it implies that consumer expects higher income and wealth in the future. Consumption expenditure might increase today, since consumers should be able to borrow against their future income and wealth, and smooth consumption over time. Or, if consumers follow a "rule of thumb", i.e., consuming current income, or if they are liquidity constrained, they might not be able to consume right away, but will be able to consumer more as their income because higher. This interpretation is supported by the analysis between consumer sentiment and consumption data.

However, Ludvigson (2004) also points out that although consumer sentiment seems to imply future income expectations, it has unique information that is not included in income data. This is related to our findings in Chapter 2. We also suggest that consumer sentiment is not a measure of animal instinct, but a reflection of information (such as news) people receive that is not included in other economic or financial variables. Based on the information, people have a better understanding of world news and big events, world economy, the economic environment around them, and their future income expectations. If we interpret consumer sentiment this way, it should have a positive relationship with both people's willingness to buy, and the willingness to invest. Moreover, its expectation component (the prediction part) might even have a stronger prediction power, due to the liquidation constraint at the current stage. Nonetheless, when consumer sentiment is higher, not only do consumers expect to have more money, they also expect other people to have more purchasing and investment power. Hence, we make the following hypothesis: higher consumer sentiment leads to positive change in house price.

We use a VAR model to study the dynamics of consumer sentiment and house price. We find that consumer sentiment is very powerful in explaining the percentage change in house price. Then we study and compare consumer sentiment within different income tiers, age groups, and regions. We find that the sentiment by mid-aged people, people with higher income, and people who live in certain regions, has the biggest explanatory power on house price change. it seems that the sentiment of people with better knowledge and experience in housing market is more valuable in predicting house price change. This leads us to wonder: in addition to consumer sentiment, by adding sentiment by professionals who work in the housing market, we might be able to find a better sentiment proxy that could have better explanatory power on house price change.

Therefore, we proposed a two-step approach to achieve this goal. The first step was to construct a better consumer sentiment index, that is housing specific. We looked into the survey questions by University of Michigan's Survey of Consumers at a micro level, and through Stepwise Regression and pairwise Granger Causality test, we are able to determine the set of questions to be used to construct a housing specific consumer sentiment.

Our second step is to construct a sentiment of people who are at the centre of the housing market. We aim at providing a sentiment measure that combines consumer sentiment (using the housing specific one we constructed), builder sentiment, realtor sentiment, and lender sentiment. Principal Component Analysis is used for the construction of the composite sentiment measure. And the measure turns out to be very successful in explaining house price change, compared with other sentiment measures.

In summary, we provide a thorough study on consumer sentiment and have some interesting results. Our findings should be valuable for both researchers and practitioners.

Chapter 2

The Determinants of Consumer Confidence: The Role of Economic Policy Uncertainty

The recent 2008 Global Financial Crisis is regarded by many economists as the worst financial crisis since the Great Depression (Pendery, 2009). Take the US as an example, the following Great Recession officially began in December 2007 and lasted for 19 months. The country experienced the most persistent and severe decline in consumption since World War II (Chatterjee and Dinda, 2015). And the recovery path was so weak, that consumption was still below pre-recession level 2 years after the recession officially ended. The impact of the Financial Crisis was also profound globally, spreading from developed countries to emerging economies. For the first quarter of 2009, the annualised rate of decline in GDP was 5.7% in US, 14.4% in Germany, 15.2% in Japan, 7.4% in the UK, and 9.8% in the Euro area (Baily and Elliott, 2009). Researchers and professionals have tried their best to untangle the underlining mechanisms behind this severe and prolonged economic downturn, and identify the important lessons that one should learn. Among these findings, most academics and policy makers agree the erosion of confidence has ensured the depth and longevity of the crisis (See, for example, Petev et al. (2011)). The problem of the role consumer confidence plays in economy has been bought back to the forefront.

Consumer confidence (which is often referred to as consumer sentiment, and these two terms will be used interchangeably throughout this thesis) captures the difference in consumer attitudes when making buying decisions, while her financial condition and the surrounding business environment stay the same. Classical finance theory assumes rationality of the consumers (Friedman, 1957). In other words, it disregards the role consumer attitudes play, with the assumption that the differences in individual attitudes would cancel out. However, the theory fails to explain many economic phenomena, such as depressions (Colander et al., 2009). In Keynes (1936)'s revolutionary work that explained the causes of the Great Depression, he proposed the idea of "animal spirits", suggesting that the change in consumer taste may influence investment. In line with this notion, Katona (1953) proposed the theory of psychological economics, and suggested that expenditures could depend on both the "ability to buy" and the "willingness to buy". While the former is an objective factor about the consumer's financial condition, the latter captures the subjective aspect about the consumer's attitude.

Since the proposal of the concept of consumer confidence and the development of its proxies, consumer confidence has been studied by a long and rich string of literature and received constant media attention for more than 50 years. However, researchers and analysts have yet to reach an consensus on many issues related to consumer confidence, such as its usefulness in explaining economic phenomena, its predictory power on future expenditure, its determinants and implications, and the underlying mechanism. In this thesis, we will revisit and try to untangle these important issues, by applying new research methods, using new data, and including new variables.

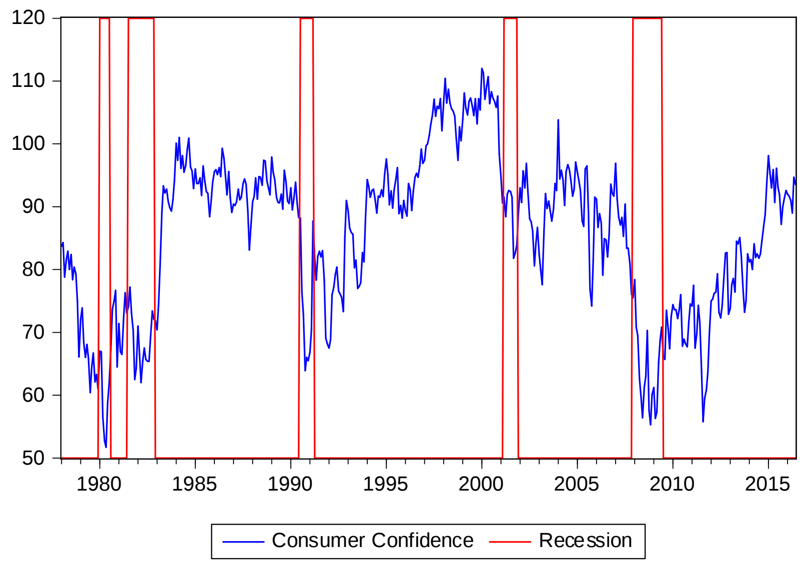
In this chapter, we focus on the following research question: what drives the changes in consumer confidence? In Katona (1972)'s opinion, consumer confidence is a unique and complex variable constantly influenced by a large range of variables, unique events, mass media, etc. For example, big events such as the 1990 Iraq War and the 2001 September 11 attacks were believed to have a large impact on consumer confidence. And these factors can only be identified afterwards. Similarly, Mueller (1963) summarised the reasons why data on consumer attitude are needed: firstly, it combines many economic factors, therefore, measuring it directly is easier and more reliable. Moreover, it is not merely a reflection of financial development. For example, it can be influenced by news, and therefore, same stimulus may be perceived differently. Finally, it shows the impact of political or economic events. Obviously, Katona and Mueller are implying that it may be impossible to study the determinants of consumer confidence since they are too many to list (with some of them nonquantitative) and too unique to study (with some of them unable to be known beforehand).

However, we can still make several observations from their discussions. Firstly, consumer confidence is probably not a subjective factor after all, but instead, it is driven by information. In other words, the rational assumption of consumers still holds. Consumer confidence is not "animal spirit" which captures short-term human emotions, but an implication of the impact of all the subtle information (including information on economy, news, political events, etc) on consumers that are relative to their buying decisions. Or in short, determinants of consumer confidence do exist. This view is supported by an empirical study by Barsky and Sims (2012).

Secondly, after carefully reading their works, we can easily identify a few variables that are good candidates as the potential determinants of consumer confidence, such as unemployment rate, stock market index, interest rate, etc. For example, in the essay "Theory of Expectations", Katona (1972) stated that "income or price expectations may be influenced by taxes, interest rates, ..., etc."

But thirdly, Katona and Mueller believe that these few macroeconomic and financial variables are unlikely to determine consumer confidence constantly well. This has been verified in literature. In fact, most research papers focused on the impact of various macroeconomic variables (such as GDP and unemployment rate) and some financial variables (such as the stock market index) in their models which predict/explain consumer confidence. Although the research methodologies and models and variables differ from each other, they seem to agree that just a few economic variables can explain consumer confidence fairly well during normal situation, but may not work well at times of economic turning points. This is quite understandable, as consumer confidence is considered as a leading economic indicator (Smith, 2009). Figure 2.1 demonstrates the relationship between consumer confidence and reces-

Figure 2.1
Relationship between Consumer Confidence and Recessions in US



Note: consumer confidence is measured by University of Michigan's Index of Consumer Sentiment (ICS), and the start and end dates of the recessions are defined by National Bureau of Economic Research.

sions from 1978 to 2016. Clearly, sentiment often led economic downturns. Recent events proved the same tendency. During the Global Financial Crisis, ICS started to fall before April 2007, while the Stock and Watson's monthly GDP estimates started to fall notably from May 2008 (Lahiri and Zhao, 2011). Since the change in consumer confidence precedes the change in economic and financial variables, how can we expect the latter to explain the former well all the time?

These three observations imply that if we find a leading variable that also contains information related to consumers' buying decisions, it may be a good candidate as the determinant of consumer confidence. Motivated by this idea, in this chapter, we propose *economic policy uncertainty* as a potential determinant of consumer confidence.

In particular, the reasons that we choose economic policy uncertainty as our main variable are as follows. Firstly, economic policy uncertainty contributes to people's expectation about government policy. And the expectation about government policy is one important kind of expectation that may have a substantial impact on consumer confidence, because it affects not only personal income expectations, but also their economic outlook (Katona, 1972).

Secondly, economic policy uncertainty may reflect information on many aspects, such as political events, terrorist attacks, and news, which are related to consumer confidence but not covered by other so called "objective" economic variables. Moreover, it may play an extremely important role in times of crises and recessions. During the Great Recession and the years following it, many policymakers, academics and business leaders have asserted that levels of policy uncertainty had gone up dramatically and contributed to the depth of the recession and the weakness of the recovery (Pastor and Veronesi, 2012). Unlike the commonly considered economic variables, economic policy uncertainty is a leading indicator that implies the lack of confidence of the government. Therefore, by including this variable, we may resolve the problem that other variables fail to explain consumer confidence well at economic turning points.

Thirdly and most importantly, we suggest that economic policy uncertainty is linked with consumer confidence through a special channel: economic policy uncertainty leads to consumer uncertainty, and higher consumer uncertainty implies lower consumer confidence. The first part of this proposal is not hard to comprehend. The uncertainty in economic policy adds ambiguity on consumers' perspective about the future, and results in uncertainty in consumer attitudes. The second part of the proposal (i.e., higher consumer uncertainty implies lower confidence) requires some explanations, which we will elaborate in the literature review. In short, in support of Curtin (2007)'s view, we believe consumer confidence measures both optimism/pessimism (i.e., the guessed trend) and uncertainty (about the guess). As a result, since higher consumer uncertainty implies higher uncertainty about the guess, it also implies lower consumer confidence.

We would also like to point out that the discussion also suggests that economic policy uncertainty has additional explanatory power to consumer confidence even when economic variables have been taken into consideration, because while the guessed trend in buying conditions can be estimated by economic variables, the uncertainty about the guess can only be approximated by variables such as economic policy uncertainty indirectly. ' To better understand the underlying mechanism driving the relationship between economic policy uncertainty and consumer confidence, we suggest the following framework:

Consumer sentiment measures two components: the objective component – expected future income, and the subjective component – uncertainty about future income. Therefore, there are two channels to influence consumer sentiment. One is the objective channel. If a variable can change consumer's expected future income, it can influence consumer sentiment. The economic and financial variables (interest rate, inflation, GDP, etc) mainly affect consumer confidence through this channel. Ludvigson (2004) holds this view.

The other channel is the uncertainty channel (or we can call it subjective channel). When uncertainty increases, based on Leduc and Liu (2016), expected demand decreases and also does not income expectation. Therefore, consumer confidence decreases. EPU explains ICS mainly through this subjective channel. This framework also implies the special and unique role EPU plays in determining ICS. And it can be used in discussing ICS's effects and transmissions.

Motivated by the theoretical evidence we discussed and aligned with intuition, we have the following hypothesis:

Hypothesis: *Higher economic policy uncertainty leads to lower consumer confidence.*

This hypothesis has some theoretical support. For example, Summers (2000) suggested that political and policy uncertainty might undermine investors' confidence. However, there does not seem to be much empirical evidence on the issue. The relationship between these two, especially the impact of policy uncertainty on confidence, remains to be studied. In this chapter, we aim at closing this gap in literature by providing some reliable empirical evidence on the role economic policy uncertainty plays on confidence. More specifically, we are aiming at answering the following research questions:

1. Whether and to what extent does economic policy uncertainty affect consumer confidence, controlling for other economic variables?

2. What are the underlying mechanisms that drive the relationship between eco-

nomic policy uncertainty and consumer confidence?

We will analyse several econometric models in order to answer the first research question, and do a series of additional analyses to answer the second one. Through the thorough data analyses and novel approaches, we can better understand the nature of the relationship between economic policy uncertainty and confidence. We believe our findings will provide valuable insights to both researchers and practitioners.

2.1 Literature Review

In this section, we give a thorough literature review on the determinants of consumer confidence, uncertainty measures and their relationship with other variables, and the relationship between consumer confidence and uncertainty. In particular, we focus on the data analysis methods, the variables included in the models, the findings, and economic implications.

2.1.1 Literature Review on the Determinants of Consumer Confidence

As we discussed before, when Katona first constructed the consumer sentiment index (ICS) in 1952 to measure consumer confidence, his assumption was that expenditures depend on not only consumers' ability to buy, but also their attitude. In 1960s, several dozens of entries (since ICS was quarterly available back then) had been collected for researchers to make meaningful quantitative analysis on consumer confidence's role. Not surprisingly, most early research had been focused on the effect of consumer confidence on consumption of durable goods. However, soon afterwards, researchers started to study the relationship between consumer confidence and many economic factors. For example, high unemployment rate should be likely to dampen consumer optimism and hence impact ICS. They started to wonder: is consumer attitude merely a reflection of financial factors, or does it include important unique information? what are the main determinants of consumer confidence?

In the 1990s, consumer confidence regained much research interest, motivated by the recession caused by the Gulf War. Researchers and practitioners were interested in the special role consumer confidence might play during crises, and what caused its large swing. Again, the 2008 Global Financial Crisis and the following Great Recession bought the studies in consumer confidence back to the forefront. In order to untangle the role consumer confidence plays, researchers further studied its determinants, and also looked for answers from international evidence.

In this sub-section, we discuss the major findings on the determinants of consumer confidence.

Models and Choices of Variables

In the early days, most research on consumer sentiment involved the application of time series regression models, with a certain proxy for consumer confidence as the dependent variable, and several predetermined macroeconomic variables as candidates for explanatory variables. However, the regression models suffer from spurious regression results (i.e., high R^2 value but actually low correlation) because the variables are often autoregressive. To correct for possible serial correlation, some researchers used Cochrane-Orcutt procedure to estimate with a correction for first-order serial correlation (Mishkin et al., 1978). In 1980, the vector autoregression (VAR) model in economics were made popular by Sims (1980), and it has been considered as one of the most successful and flexible models for analysing multivariate time series. In the 1990s, researchers started to apply VAR models to financial problems (Hamilton, 1994). The study on consumer confidence is no exception. Starting from 1990s, researchers rely on VAR models to study the same problem.

Katona always stressed the importance of unique events in the determination of consumer sentiment. However, in his discussions, variables such as income, stock prices, and the rate of inflation, seem to influence consumer mood systematically. Until now, there is no consensus on the "best" set of determinants. This is because firstly, a wide range of variables could influence consumer confidence, and secondly, researchers may reach different conclusions when their models are slightly different (for instance, use the level of variables or their first differences). Here is a discussion on the most common explanatory variables. The definitions of variables are from investopedia (http://www.investopedia.com/).

Unemployment Rate

The national unemployment rate is defined as the percentage of unemployed workers in the total labor force. Mueller (1963) used time series regression model to study the relationship between ICS and the variables related to unemployment and disposable income. She found that unemployment rate explained 17% of the variability in ICS (with a negative coefficient). She explained that unemployment impacted ICS by dampening of consumer optimism.

Adams and Green (1965) considered a much wider set of candidate variables that might be useful in explaining ICS. From their regression results, change in unemployment rate explained 52.8% of the variability in ICS. They suggested that attitudes were highly correlated with indicators relating to employment conditions.

Unemployment rate has also been included in most of the more recent works, and has been repeatedly proved to have a negative impact on consumer confidence (Fuhrer, 1993; Ludvigson, 2004, for example). Unemployment rate is related to the future business conditions and personal finance outlook. Higher unemployment rate leads to lower consumer optimism on future business conditions. It also implies higher possibility of unemployment of the consumer, which leads to lower income expectation. As a result, it impairs buying intentions.

Stock Market Index

Stock market index is typically a weighted average of the prices of selected stocks. It is used by investors and financial managers to describe the market. Hymans et al. (1970) were the first to include stock market index in the model. They suggested that stock prices change in the previous time period, income ratio, a variable related to inflation rate, and the ICS value in the previous time period, are all useful predictors for ICS, with adj-R^2 being 0.796. Note that they did not find stock market index level to be useful. However, Juster et al. (1972) found that stock market index level, together with the change in the index, are both useful in explaining ICS.

Huth et al. (1994) used VAR and Cross-Correlations of ARIMA Innovations to analyse the data, and found that the following variables Granger cause the confidence index: CPI, Standard & Poors 500, Dow Jones Average, and Single Family Housing

Starts. Surprisingly, they found Unemployment Rate is Granger caused by both ICS and its component, not vice versa.

Jansen and Nahuis (2003) performed Granger causality tests on the model containing log of the stock price index and the consumer confidence index in eleven European countries. They found that stock returns generally Granger cause consumer confidence, at a very short time horizon (the results were significant in 8 countries when considering a 2 week lag, and only 4 remain significant when the lag is a month).

Allis and McCallig (2007) studied the regression of Ireland's consumer sentiment on stock market returns only, and found the coefficients were positive and significant.

To summarise the common findings, stock market index is expected to have a positive impact on consumer confidence. Stock market index is related to investment returns (and hence income), and moreover, it is an indication of investment sentiment. Directly, higher stock market index reflects higher investor sentiment, and investor sentiment and general consumer sentiment are often highly correlated. More fundamentally, higher investor sentiment implies optimism on the state of its economy, which indicate more income, and therefore, boosts consumer confidence.

Inflation Rate and Consumer Price Index

In economics, inflation is a sustained increase in the general price level of goods and services in an economy over a period of time. Clearly, based on this definition, different measures are available. Hymans et al. (1970) used the ratio of implicit price deflator for personal consumption expenditures and the average deflator of the eight previous periods in their regression model, and found a negative relationship between this variable (which is related to inflation) and consumer confidence.

Juster et al. (1972) studied the similar model with a more extensive choices of inflation measures. The dependent variable is the level of ICS, and the explanatory variables include the lagged value of the dependent variable, stock market index, change in stock market index, and various inflation measures, and their model generated $R^2 = 0.903$. They found that inflation impacted consumer confidence. However, they also found that the results were sensitive to the selection of an inflation measure, and the effects of inflation might be different in different time periods.

One limitation of Hymans et al. (1970) and Juster et al. (1972) is that they did not include unemployment rate in their model. Lovell (1975) chose a more standard measure of inflation: the annual percentage change in the consumer price index, and their model covered a wider selection of explanatory variables, including annual inflation rate, unemployment rate, the annual percentage change in the stock market index, and the lagged value of ICS. They also calculated the influence on ICS when inflation rate and stock market index changed using real data in 1974, and concluded that ICS was much more sensitive to inflation than to fluctuations in the stock market.

Later, with the development of methodology, Lovell and Tien (1999a) followed the similar approach, but used a first order autoregressive process to correct for autocorrelated error terms. His model considered inflation rate, change in inflation rate (not significant), unemployment rate, change in unemployment rate, change in GDP, stock market index, and the error correction term. they reached the same conclusion as before.

Abeele (1983) dealt with the autocorrelation problem in the residual, by considering Cochrane-Orcutt iterative procedure. He used lagged values of the following variables: the stock exchange index, the unemployment rate, disposable income, and the consumer price index. He found that variables related to consumption prices and stock prices yield the best regressors, while the income and unemployment are less important. He also observed that the findings were consistent among several countries.

High inflation may signal a business cycle expansion, and high growth in the consumer price index can be simply one manifestation of high growth in aggregate demand. Therefore, higher price is likely to lead to lower consumer confidence. And the increase in inflation rate, which can be calculated as the change in consumer price index, is also likely to lead to the decrease in consumer confidence. Actually, the summation of the unemployment rate and the annual rate of inflation is defined as "economic discomfort index" by Arthur Okun. It approximates the impact of economic conditions on the consumer. Clearly, we expect a negative relationship between economic discomfort and consumer confidence.

Interest Rate

Throop (1992) used an expanded Error Correction Model (ECM) to find the causes of ICS. He started from Mishkin's model, and then added some more variables, such as oil price and interest rate. He also disintegrated the ICS to the current condition component (CIND) and the expectation component. He found that the change in short-term interest rate and the change in unemployment rate are important predictors of CIND, but only the change in interest rate are important for main ICS.

Fuhrer (1993) also considered a first-order ECM model, in addition to a separate Cointegration Model. The independent variables he considered include disposable income, unemployment rate, inflation rate and interest rate, and the large fraction of the information in sentiment is explained and predicted by these variables. He also found that "the largest errors in predicting sentiment occur around business cycle turning points".

Acemoglu and Scott (1994) selected variables lagged dependent variable, interest rate, inflation rate and current change in housing wealth, and were able to explain as large as 82% of the variation in ICS. Olowofeso and Doguwa (2012) considered a wide range of macroeconomic variables, and found exchange rate and interest rate are negatively affecting consumer confidence.

In summary, short term interest rate has additional explanatory power on consumer confidence in some models. In general, changes in interest rates have different effects on consumer spending. On one hand, lower short term interest rate implies lower incentive to save, as the future net benefits are discounted with a lower discount rate. Therefore, it encourages consumer spending and stimulates investment. On the other hand, lower interest rate implies the government's effort to promote consumption and investment, hence it is an implication of lower willingness to buy. But how well the incentive works remains unknown. Generally speaking, the incentive often successfully promotes spending, and hence lower interest rate leads to higher consumer willingness to buy.

Gross Domestic Product or Industrial Production Index

Gross domestic product (GDP) is the monetary value of all the finished goods and services produced within a country's borders in a specific time period. It is a broad measurement of a nation's overall economic activity. Since GPD is only calculated on a quarterly basis, the monthly Industrial Production Index (IPI) is often used as its proxy. In particular, IPI is an economic indicator that is released monthly by the Federal Reserve Board, which measures the amount of output from the manufacturing, mining, electric and gas industries. In the recent years, several research papers have included GDP or IPI in their models as potential determinants of consumer confidence. For example, Lovell and Tien (1999b) found that the growth rate of GDP, together with the change in stock market index and the unemployment rate, explain consumer confidence. In theory, higher GDP implies better business conditions, and hence higher consumer confidence.

Disposable Income

Disposable personal income is the amount of money that households have available for spending and saving after income taxes have been accounted for. Intuitively, consumer confidence should be closely linked with consumer's financial conditions and financial outlook. However, from the early days, researchers had found that income alone was not a very good predictor of the ICS (Mueller, 1963; Abeele, 1983, for example). This is because income is more related to people's ability to buy, not the willingness to buy. On the other hand, the ratio of deflated personal disposable income in survey quarter to highest previous quarterly level (or to the average of previous levels) was found to be a better explanatory variable (Mueller, 1963)(Hymans et al., 1970). Nonetheless, many researchers still included disposable income or its change in their models on the determinants of consumer confidence (Throop, 1992; Van Oest and Franses, 2008, etc.).

Other Variables

Researchers also considered many other variables that are potentially useful in determining consumer confidence. Some are related to employment conditions, such as length of average work week in manufacturing industry, new hiring rate, etc (Adams and Green, 1965), some are related to personal financial conditions, such as household liabilities and financial-asset holdings (Mishkin et al., 1978)

Golinelli and Parigi (2004) compared the results for more regions, including

France, Germany, Italy, UK, USA, Japan, Canada and Australia. They considered the following explanatory variables: GDP change, inflation rate, interest rate, change in stock market index, unemployment rate, lagged consumer confidence, exchange rate against the US dollar, employment-population ratio, and output gap, etc. They found that the results were country specific. The driving force of consumer confidence cannot be simply summarised. Moreover, Özerkek and Çelik (2010) studied the role of government spending on consumer confidence in six emerging market countries (Brazil, Czech Republic, Hungary, Poland, South Africa and Turkey), and confirmed the causal relationship.

Dées and Brinca (2013) searched for variables that Granger cause consumer confidence in the US and Europe. Among the variables they considered, the real consumption expenditures and real equity prices cause consumer confidence change in the US, while logged income, unemployment rate, and foreign confidence cause consumer confidence change in the Euro area.

We have discussed the economic variables (such as unemployment rate and inflation rate) and financial variables (such as stock price) that are often considered as determinants of consumer confidence. Researchers have also considered several variables that are related to news, political events, etc. For example, Ramalho et al. (2011) discussed the variables that influence consumer confidence in Portugal. In addition to the economic variables commonly used in previous papers, they added the variable electoral cycle into consideration, and confirmed its influence on consumer confidence.

Intuitively, news may also affect consumer sentiment. Pruitt et al. (1988) proposed an novel approach to studying the effect of media presentation on people's attitude. They asked 120 students to read news on the same issue from different resources, and then asked them to do a survey similar to the questions for calculating ICS. Their finding was consistent with the intuition. Van Raaij (1989) provided some theoretical analysis on this issue. Blood and Phillips (1995) found that recession headlines influenced consumer confidence. Doms and Morin (2004) pointed out that the news media affects consumers' perceptions of the economy through several channels. Later on, Horner (2008) examined the role of mass media on consumer confidence in his PhD thesis. He claimed that attention to news about the economy was a significant predictor of individual consumer confidence. Hollanders and Vliegenthart (2011) studied the influence of negative newspaper coverage on consumer confidence in Netherland, through a computer-assisted content analysis and a VAR model. They provided a very interesting insight: the effect of media coverage seems to change in time. The influence is bigger during a boom and bust cycle. Nguyen and Claus (2013) considered not only the bad news, but also the good news. They found that their effects are asymmetric: "consumers react to bad but not to good news". On the contrary,Lahiri and Zhao (2013) noted that sentiment measures do not seem to be direct reflections of political and business news. Most recently, Igboayaka (2015) tried to use a data extraction tool called NetBase Insight Workbench to mine data from the social media networks, and measure consumer confidence from the results.

There were not many papers focused on this most recent Global Financial Crisis. Petev et al. (2011) looked into data for different income groups when studying consumption in the Great Regression, and discovered that ICS recovered sharply for the top income group, but not for the bottom one. Hollanders and Vliegenthart (2011) also studied the special role of media coverage in the most recent credit-crisis, and found that it seems to have much more impact than before.

In summary, while there are no consensus on which economic variables are the most important determinants of consumer confidence, there seem to be some agreements on the following points of views:

- A small set of macroeconomic and financial variables (such as personal disposable income, unemployment rate, inflation rate, interest rate, stock price, etc) are normally able to explain a huge part of variability in the consumer confidence index (with $\bar{R}^2 > 90\%$) , and predict a relatively large part as well (with $\bar{R}^2 > 50\%$).

- Under normal circumstances, consumer sentiment often bears a stable relationship to these economic and financial variables.

- However, at times of major economic or political events, the prediction may divert from the true consumer confidence levels, and consumer confidence provides useful and unique information (Berry and Davey, 2004; Fuhrer, 1993; Throop, 1992). Moreover, Fuhrer (1993) and Souleles (2004) both pointed out that sentiment might behave differently in different business cycles.

- News also have an influence on consumer confidence.

2.1.2 Literature on Uncertainty

Uncertainty is a broad topic. For economic related uncertainty, researchers have proposed concepts such as policy uncertainty and macroeconomic uncertainty, and studied their relationships with other economic variables. For instance, Antonakakis et al. (2012) studied the dynamic co-movements between stock market returns and policy uncertainty, and concluded that Increased stock market volatility increases policy uncertainty and dampens stock markets returns. Moreover, Kang and Ratti (2013) concluded that oil price shocks and economic policy uncertainty are interrelated and influence stock market returns. On the other hand, Li et al. (2013) found there were weak causal relationship between Economic Policy Uncertainty and stock returns in China and India.

Bhagat and Obreja (2013) found empirically that uncertainty had a strong negative impact on corporate employment and investment. Istrefi and Piloiu (2014) used structural VARs to show that both long- and short-term inflation expectations are sensitive to policy-related uncertainty shocks. On the contrary, Jones and Olson (2013)'s multivariate DCC-GARCH model revealed that the sign of the correlation between macroeconomic uncertainty and inflation changed from negative to positive during the late 1990s, whereas the correlation between uncertainty and output is consistently negative.

Ever since the publication of Economic policy uncertainty index (Baker et al., 2015), researchers have studied its relationship with stock market (Baker et al., 2013; Antonakakis et al., 2012), recessions and business cycles (Baker et al., 2012; Benati, 2013; Azzimonti and Talbert, 2014), unemployment (Caggiano et al., 2013; Bakas et al., 2016), volatility, macroeconomic uncertainty and other uncertainty measures

(Bailey et al., 2012; Amengual and Xiu, 2014; Creal and Wu, 2014), etc. There is some evidence that shows that economic policy uncertainty has a negative relationship with the stock market performance, a positive relationship with unemployment rate, and contributes to the prolonged recessions.

2.1.3 Relationship between Consumer Confidence and Uncertainty

While many researchers (Tobin (1972), Lemmon and Portniaguina (2006) among others) view consumer confidence as a measure of optimism/pessimism on business conditions, many others suggest that consumer confidence measures uncertainty. For example, Juster and Wachtel (1972) claimed that " the sentiment index really stands for uncertainty". Similarly, Mishkin et al. (1978) suggested that "sentiment measures consumers' perceptions of the probability of financial distress", and Carroll et al. (1994) also concluded that sentiment is, in part, a measure of uncertainty. Throop (1992) and many others are also supporters of this view. There are also many studies that did not distinguish these two concepts. For example, Katona (1951) made the following tentative generalisation: "pessimism, insecurity, expectation of income declines or bad times in the near future promote saving". Here, insecurity probably stands for uncertainty. However, there is actually a clear distinction between optimism/pessimism and uncertainty. To put it simply, the former refers to the "expected value" of the assessment and prediction on personal financial and general economic conditions, while the latter refers to the "variance" of such assessment and prediction. We think consumer confidence measures both. This view is shared by Curtin (2007). He suggested that the forecast of the future buying conditions has two components – the guessed trend, and the uncertainty about the guess.

There are limited research on the relationship between consumer confidence and economic policy uncertainty. Probably the closed one was Baker's paper, which points out the similarity of the two indexes (Baker et al., 2015).

However, from the existing literature we discussed in the previous two sections, we can conclude that there are at least some indirect links between consumer confidence and uncertainty: for instance, both consumer confidence and uncertainty have a close relationship with stock market index. Higher uncertainty leads to lower stock market index, which leads to lower consumer confidence. And similarly, they are both correlated with unemployment, inflation, and other variables. On the other hand, consumer confidence is closely linked with media coverage. Uncertainty can be measured by counting the words "uncertainty" on newspapers. Therefore, through the media channel, uncertainty can impact consumer confidence. These findings provide some theoretical support to our hypothesis.

However, the limitations of the literature are also obvious. In the existing models that study consumer confidence, the researchers often focused on a few macroeconomic and financial variables. The only exception was that in a few studies, they also examined the role of media data. Nonetheless, the relationship between uncertainty and consumer confidence is yet to be studied. There are no empirical evidence on this issue. Moreover, most studies were based on the US data only. Whether their findings are country specific or universal is yet to be examined. Our study will fill in these gaps in literature by examining the relationship between economic policy uncertainty and consumer confidence directly through a thorough empirical study in two largest economies in the world, US and Europe.

2.2 Data

Our main focus is to study the influence of economic policy uncertainty on consumer confidence when other economic variables are controlled for. To do this, we first need to introduce what control variables we decide to include in our models, and how the two main variables, which measure economic policy uncertainty and consumer confidence, respectively, are calculated.

Unlike most existing studies, which focus on the US data only, we analyse data for two largest economies in the world, United States and Europe, respectively. By comparing the similarities and differences in the findings between these two areas, we can better understand the role economic policy uncertainty plays on consumer confidence.

2.2.1 Measurements of Consumer Confidence

US Consumer Confidence Measure

For the US, University of Michigan's Consumer Sentiment Index (ICS) is used as a proxy for consumer confidence in this study. Although there is no consensus on how to measure consumer confidence, ICS is the most widely used proxy for consumer confidence in literature. It is the first survey based index that aims at measuring consumer confidence, and has been proven useful in serving this goal. The index has been generated based on at least 500 consumers' phone responses to five questions about current and expected personal/overall economic conditions. It was first introduced in 1946 and provided annually. It became quarterly available from 1952 to 1977, and monthly available since 1978. The data and methodology are available from the Survey Centre's website (`data.sca.isr.umich.edu`). In brief, ICS is calculated based on answers to the following five questions:

Q1 = "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"

Q2 = "Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

Q3 = "Now turning to business conditions in the country as a whole–do you think that during the next twelve months we'll have good times financially, or bad times, or what?"

Q4 = "Looking ahead, which would you say is more likely–that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?"

Q5 = "About the big things people buy for their homes–such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?"

Questions Q1 through Q5 (expect for Q4) are multiple choice questions, whose choices include favourable, unfavourable, neutral, and uncertain opinions. On the other hand, Q4 is an open-end question. But still, the interviewers group the answers as favourable, unfavourable, neutral, and uncertain replies.

First, for each of the five index questions, the relative score is calculated, by taking the percent giving favourable replies minus the percent giving unfavourable replies, plus 100. We denote the relative scores as y_1, y_2, ..., y_5. Clearly, Q1 and Q5 are related to the current situation, while the rest three questions are related to future expectations. Officially, the Index of Current Economic Conditions (ICC) and the Index of Consumer Expectations (ICE) are calculated as follows:

$$ICC = \frac{y_1 + y_5}{2.6424} + 2.0, \qquad ICE = \frac{y_2 + y_3 + y_4}{4.1134} + 2.0.$$

In other words, ICC is the current component of ICS, and ICE is the expected component of ICS. Similarly, ICS is calculated using the following formula:

$$ICS = \frac{y_1 + y_2 + y_3 + y_4 + y_5}{6.7558} + 2.0.$$

We can observe that all the related questions are given equal weights when ICS and its current/expected components are calculated.

The questions and components are summarised in Table 2.1.

Table 2.1
US Consumer Confidence Measure (ICS) and its Components

<table>
<tr><th>Aggregated Index</th><th>Decomposition</th><th>Further Decomposition</th></tr>
<tr><td rowspan="5">Index of Consumer Sentiment ICS $\sim (y_1 + y_2 + y_3 + y_4 + y_5)$</td><td rowspan="2">Current Component ICC $\sim (y_1 + y_5)$</td><td>Personal Finance Current (y_1)</td></tr>
<tr><td>Buying Conditions (y_5)</td></tr>
<tr><td rowspan="3">Expected Component ICE $\sim (y_2 + y_3 + y_4)$</td><td>Personal Finance in 12 Months (y_2)</td></tr>
<tr><td>Business Condition in 12 Months (y_3)</td></tr>
<tr><td>Business Condition in 5 Years (y_4)</td></tr>
</table>

Note: x_i denotes relative scores of question Q_i $(i = 1, 2, ..., 5)$.

European Consumer Confidence Measure

For Europe, Consumer Confidence Index (CCI) by European Commission is used as the measurement of consumer confidence in this study. The harmonised surveys are carried out at national level by partner institutes for different sectors of the economies (including consumers, industry, services, retail trade and construction) in the European Union (EU) and in the applicant countries. The surveys are conducted according to a common methodology, which consists essentially of harmonised questionnaires and a common timetable. EU aggregate replies to the questionnaires are calculated as weighted averages of the country-aggregate replies. The weights are the shares of each of the Member States in an EU reference series.

The survey on consumers was launched in 1972. The sample sizes differ by country, but for the whole EU, around 41060 consumers are interviewed monthly. the index is calculated from the answers to four forward looking questions. The data are available from European Commission's website (`ec.europa.eu`). In brief, for each country, CCI is calculated from the answers to the following four questions.

Q1 = "How do you expect the financial position of your household to change over the next 12 months?"

Q2 = "How do you expect the general economic situation in this country to develop over the next 12 months?"

Q3 = "How do you expect the number of people unemployed in this country to change over the next 12 months?"

Q4 = "Over the next 12 months, how likely is it that you save any money?"

The relative score (which is called "balance" in the official guide) of question i is calculated as follows:

$$x_i = PP + \frac{P}{2} - (\frac{N}{2} + NN),$$

where PP, P, N, and NN denote the percentages of respondents having chosen respectively the option "very positive", "slightly positive", "slightly negative" and "very negative". And CCI is the arithmetic average of the balances, i.e.,

$$CCI = (y_1 + y_2 - y_3 + y_4)/4.$$

Note that the sign before y_3 (unemployment rate) is negative.

Obviously, unlike ICS, all the four questions used to calculate CCI are forward looking. Since CCI is the most commonly used consumer confidence measure in Europe, we will use use it in our main analysis. However, in the additional analyses section, in order to compare the effects of EPU on current and expected components, we collected balance data for the following additional questions included in the same consumer questionnaire, which are quite similar to the US questions on current situation.

Q5 = "How has the financial situation of your household changed over the last 12 months?"

Q6 = "In view of the general economic situation, do you think that now it is the right moment for people to make major purchases such as furniture, electrical/electronic devices, etc.?"

Therefore, we can construct the US-equivalent current component of consumer confidence, the US-equivalent expected component of consumer confidence, and the US-equivalent ICS as follows:

$$\text{ICC} = y_5 + y_6, \quad \text{ICE}_{\text{equiv}} = y_1 + y_2, \quad \text{ICS}_{\text{equiv}} = y_1 + y_2 + y_5 + y_6.$$

We would like to point out that in the European survey, there is no equivalent question to US Q4. The questions used to calculated CCI and the questions that are similar to the ones used to calculate ICS, are summarised in Table 2.2.

Table 2.2
European Consumer Confidence Measure (CCI) and its Components

Aggregated Index	**Decomposition**	**Further Decomposition**
Consumer Confidence Index CCI $\sim (y_1 + y_2 + y_3 + y_4)$	Current Component ICC $\sim (y_5 + y_6)$	Personal Finance Current (y_5)
		Buying Conditions (y_6)
	Expected Component ICE $\sim CCI$	Personal Finance in 12 Months (y_1)
		Business Condition in 12 Months (y_2)
$\text{ICS}_{\text{equiv}} \sim (y_1 + y_2 + y_5 + y_6)$		Unemployment Rate in 12 Months (y_3)
	$\text{ICE}_{\text{equiv}} \sim (y_1 + y_2)$	Saving Money in 12 Months (y_4)

Note: x_i denotes balance scores of question Q_i $(i = 1, 2, ..., 6)$, which can be found in the Data section.

Finally, we would like to point out that the names of the two components could be a bit misleading. In fact, the "current" component is like the more "objective" component, which is based on the known facts or expectations (such as the current income, or the current business condition). On the other hand, the "expected" component does not provide an unbiased expectation. In fact, it is more like the "subjective" component, which is based on consumers' predictions and guesses (such as future income, etc). Therefore, after studying the determinants of ICS and CCI, it is worth studying the determinants of their current and expected components, and compare the results. We will do this in section 2.5.1.

2.2.2 Measurements of Economic Policy Uncertainty

We use the Economic Policy Uncertainty Index (EPU) as a proxy for economic policy uncertainty in this study. EPU is proposed and provided by a group of scholars from Northwestern, Stanford and University of Michigan monthly for many countries. The data and methodology are available from the EPU website (`www.policyuncertainty.com`).

US Economic Policy Uncertainty Measure

To measure policy-related economic uncertainty in the US, the above mentioned scholars construct an index from three types of underlying components: newspaper coverage, disagreement among economic forecasters for the US, and the number of federal tax code provisions set to expire in future years.

The first component, news coverage about policy-related economic uncertainty, has the highest weight of 0.5 when calculating the overall index. It is an index of search results from 10 large newspapers. Month-by-month searches of each paper is performed, starting in January of 1985, for terms related to economic and policy uncertainty. In particular, they search for articles containing all the following three types of terms: the term related to uncertainty ('uncertainty' or 'uncertain'), the term related to the economy ('economic' or 'economy') and one or more of the terms related to policy ('congress', 'legislation', 'white house', 'regulation', 'federal reserve', or 'deficit'). Results are normalised to an average value of 100 from January

1985 through December 2009.

There are two components drawn on the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters, each with a weight 1/6. The second component is the dispersion in the forecasts of purchase of goods and services by governments, and the third component is the dispersion in the forecast of consumer price index (CPI).

Finally, the fourth component is the temporary tax measures, also with a weight 1/6, which are a source of uncertainty for businesses and households because Congress often extends them at the last minute, undermining stability in and certainty about the tax code.

For the US, the overall EPU index is a weighted average of the four components. Both the EPU index values and the component values are provided for free monthly. In addition, categorical data are also available, which include a range of sub-indexes based solely on news data. Each sub-index requires our economic, uncertainty, and policy terms as well as a set of categorical policy terms. In other words, the searched results from a certain category are a subset of the results from the news-based component. However, the searched results from two categories may (partially) overlap with each other. The US EPU, its components, and categorical data, are summarised in are summarised in Table 2.3.

Table 2.3
US Economic Policy Uncertainty Measure (EPU), its Components, and Sub-categories

<table>
<tr><th>EPU</th><th>EPU Components</th><th>News Based Categories</th><th>Category Keywords</th></tr>
<tr><td rowspan="12">EPU = $\frac{1}{2}x_1 + \frac{1}{6}x_2 + \frac{1}{6}x_3 + \frac{1}{6}x_4$</td><td rowspan="3">News Based Policy Uncertainty Index ($x_1 \sim c_1$)</td><td>Economic Policy Uncertainty (c_1)</td><td>economic, policy, uncertainty</td></tr>
<tr><td>Monetary policy (c_2)</td><td>c_1+ the fed, central bank, etc</td></tr>
<tr><td>Taxes (c_3)</td><td>c_1+ tax, taxation, etc</td></tr>
<tr><td rowspan="3">Fed/State/Local Purchase disagreement (x_2)</td><td>Government spending (c_4)</td><td>c_1+ government spending, etc</td></tr>
<tr><td>Health care (c_5)</td><td>c_1+ health insurance, etc</td></tr>
<tr><td>National security (c_6)</td><td>c_1+ terrorism, war, etc</td></tr>
<tr><td rowspan="3">CPI disagreement (x_3)</td><td>Entitlement programs (c_7)</td><td>c_1+ welfare reform, etc</td></tr>
<tr><td>Regulation (c_8)</td><td>c_1+ regulation, etc</td></tr>
<tr><td>Trade policy (c_9)</td><td>c_1+ import/trade duty, etc</td></tr>
<tr><td rowspan="3">Tax expiration (x_4)</td><td>Sovereign debt, currency crises (c_{10})</td><td>c_1+ currency crisis, etc</td></tr>
<tr><td>Financial Regulation (c_{11})</td><td>c_1+ banking supervision, etc</td></tr>
<tr><td>Fiscal Policy (c_{12})</td><td>c_1+ fiscal stimulus, etc</td></tr>
</table>

European Economic Policy Uncertainty Measure

For countries other than the US, the EPU indexes are all news based only. The calculation method is in the same manner as the news based EPU index for the US (i.e., x_1). For the European-wide EPU index, results from 10 European newspapers (two newspapers per country, for Germany, France, Italy, Spain, and UK) are averaged with equal weights.

2.2.3 Control Variables

If we only consider two variables (i.e., ICS/CCI and EPU) in our model, we are disregarding the possibility that the information contained in uncertainty is already contained in other variables. Therefore, we also include macroeconomic and financial variables that are most widely used in the models on the determinants of consumer confidence (as discussed in the Literature Review section). In particular, we carefully choose the following variables:

- Disposable Personal Income (INC): seasonally adjusted monthly data of disposable personal income per capita at constant price. Unfortunately, the Income data for Europe is only available quarterly. We obtain monthly estimates by taking weighted averages between two values in adjacent quarters (i.e., by linear interpolation method).

- Industrial Production Index (IPI): monthly data that measures the real production output of manufacturing, mining, and utilities. It can be used as a proxy for gross domestic product (GDP), which is only available quarterly.

- Consumer Price Index (CPI): monthly data that measures changes in the price level of a market basket of consumer goods and services purchased by households. Its first difference denotes inflation rate (INF). Note that this is different from the third component of EPU, because in the EPU, the dispersion (or variance) of CPI instead of the value is used.

- Interest Rate (INT): monthly data of the 3-Month Treasury Bill Rate for the US, and European Central Bank's 3-month Interbank offered rate for Europe.

- Stock Market Index (STO): month-end S &P 500 Composite Price Index for the US, and S &P EUROPE 350 INDEX for Europe.
- Unemployment Rate (UNE): monthly data that measures percentage in labour force that are unemployed.

Data for all the six control variables are downloaded from DataStream.

2.2.4 Summary Statistics

At this stage, we focus on the aggregated main variables (ICS/CCI, and EPU) only, but not their components. For both US and Europe, we collect monthly data (including two main variables, ICS/CCI and EPU, and six control variables) from the earliest date when all data became available, to the most recent possible date. The dataset starts in January 1985 and ends in May 2016 for the US (377 observations in total), and from January 1991 to April 2016 for Europe (304 observations in total).

Before we provide summary statistics, we first explain how we process the data. Our first step is to take the natural log for INCOME and IPI. There are many reasons for this. Firstly, it makes perfect sense Intuitively. An income increase from 0 to 1, and an income increase from 10000 to 10001, should have different effects. Similarly, the impact scale of the change in IPI is not linear as well. On the other hand, it is a better approximation that IPI (and GDP) changes multiplicatively than that it changes additively. Secondly, in a technical point of view, these variables are likely to be heteroskedastic, and not normally distributed. Taking the logs might resolve these issues, and hence make regression results believable. Thirdly, it is a common practice in econometrics. Many elasticity models (log-log models), linear-log models, or log-linear models have become a standard. In these models, variables such as income, expenditure, GDP are logged. In literature regarding consumer confidence in particular, many research papers also chose to take logs of these variables.

Then, we determine whether to use the level or the first difference of each variable. Since there is no consensus among the researchers, we decide to make our decisions based on both the variables' stationarity, and their actual meanings. If a series is not stationary, indicated from the unit root test results, the regression results may be spurious (i.e., apparently high degree of fit but actually low correlation) (Granger and Newbold, 1974). However, there are also arguments on whether each series has to be stationary in regression or vector autoregression models, because the meaningfulness of the equations is also very important. Therefore, for each non-stationary variable, we will only use its first difference in our models if it makes sense.

The unit test results for both US and Europe are shown in Table 2.4. From the results, we can see that the results for US and Europe are quite consistent. At test critical value 10%, all the control variables except for the unemployment rate are nonstationary, while EPU, ICS and UNE are stationary. The first differences for all the variables are stationary. We have tried the model with levels of all variables, and the results are indeed spurious (adj-R^2 >> Durbin-Watson stat d, see Granger and Newbold (1974); Min (2019)). Among the nonstationary control variables, for some of them, it makes sense to use their change to explain the level of ICS. For example, income itself has an increasing trend in a long run, but it does not imply ICS should have the same trend. The change in income shows how it derives from the ordinary (increasing) trend, and this value should have an influence on the value of ICS. The same is true for CPI, IPI and Stock Market Index, which all have an increasing trend in the long run. On the other hand, we do not expect interest rate to have a monotonic trend in the long run (although the data for our chosen period seem to show a decreasing trend). Based on the stationarity results and the nature of the variables, we finally decide to use the first differences for these four control variables (CPI, logged Income, logged IPI, and Stock Market Index), and use the levels for four other variables (EPU, ICS, unemployment rate and interest rate).

In summary, our model includes the following seven variables: ICS/CCI, EPU, INF (ΔCPI), $\Delta \log$(INC), $\Delta \log$(IPI), INT, ΔSTO, and UNE. We plot the time series for all the variables in Figure 2.2. The summary statistics are reported in Table 2.5. From the figures, we can see that for both countries, after taking the first differences, variables INF, $\Delta \log$(INC), $\Delta \log$(IPI), and ΔSTO no longer seem to be autocorrelated, have a monotonic trend, or be nonstationary. Some control variables have large Kurtosis. This is often due to the fact that the majority of the

Table 2.4
Augmented Dickey-Fuller (ADF) Unit Root Test Results

Panel A: ADF Unit Root Test Results for US

Null Hypothesis: There is a unit root.							
ICS	EPU	CPI	log(INC)	log(IPI)	INT	STO	UNE
p-value for the levels of variables:							
0.019	0.008	0.85	0.61	0.42	0.50	0.93	0.058
p-value for the first differences of variables:							
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: ADF Unit Root Test Results for Europe

Null Hypothesis: There is a unit root.							
CCI	EPU	CPI	log(INC)	log(IPI)	INT	STO	UNE
p-value for the levels of variables:							
0.098	0.0008	0.75	0.75	0.30	0.39	0.30	0.077
p-value for the first differences of variables:							
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010

Note: ICS = Index of Consumer Sentiment for US by University of Michigan. CCI = Consumer Confidence Index for Europe by European Commission. EPU = the Economic Policy Uncertainty Index. CPI = Consumer Price Index. (INF = inflation rate, or first difference of CPI.) INC = disposable personal income. IPI = Industrial Production Index. INT = 3-Month interest rate. STO = Month-end Stock Market Index. UNE = unemployment rate. All are monthly data from Jan 1985 to May 2016 for US and from Jan 1991 to April 2016 for Europe. Automatic lag length selection based on Schwarz information criterion: 0 to 16.

values are concentrated around the mean and there are occasional values far from the mean.

Based on the information from the Data Section, we can calculate the theoretical range of ICS for US. The relative score of a question can range from 0 (100% unfavourable answers) to 200 (100% favourable answers). According to the equation in which ICS is calculated from the relative scores, ICS can range from 2 to 150, when neutral value 76 (when the favourable and unfavourable replies are equal). From Table 2.5 (Panel A), we can observe that the actual ICS ranges from 55.3 (indicating 28% more unfavourable answers to favourable ones) to 112.0 (indicating 48.6% more favourable answers to unfavourable ones), with average value 87.4 (indicating 15% more favourable answers than unfavourable ones). This implies that in general, more consumers have a positive opinion. The Skewness is -0.47 (comparing with Skewness of 0 for normal or other symmetric distributions), indicating the left tail is longer and flatter. This implies that in cases when ICS is lower than average, people can be quite pessimistic, and ICS can be really low (note that the lowest value is 32.1 points below average). These extremely low ICS values often correspond to crises or big events. On the other hand, when ICS is higher than average, it tends to be slightly higher than average (note that the largest value is only 24.6 points above average). This means that unlike crises, there are not "golden times" during which consumers are extremely optimal. Its Kurtosis is 2.88, close to that of a normal distribution (which is 3).

Based on the discussion in the Data Section, EPU does not have a clear range. On one hand, the more news articles on related issues, the higher EPU is. It does not seem to be bounded. On the other hand, the normalisation process is complicated, which makes the discussion on the range impossible. What we can know from the calculation process is that 100 seems to be a reference point as an average EPU value. In fact, it shows in Table 2.5 that EPU ranges from 57.2 to 245.1, with mean 107.6. The positive Skewness (0.98), indicating a much long and flatter right tail. This implies that when uncertainty is high, the data takes larger range. This means that in certain cases, the economic policy is extremely uncertainty, deviating from the average. These cases probably correspond to crises or big events that result in huge uncertainty about economic policies. Its Kurtosis, 3.80, is also not quite far from a normal distribution.

For all the data, the Jarque-Bera statistic results did not reject the hypotheses of normal distributions.

Table 2.5
Summary Statistics

Panel A: Summary Statistics for US

	ICS	EPU	INF	$\Delta\log(\text{INC})$	$\Delta\log(\text{IPI})$	INT	ΔSTO	UNE
Mean	87.4	107.6	0.36	0.0014	0.0016	3.57	4.99	6.10
Median	90.4	100.4	0.40	0.0016	0.0019	3.96	6.86	5.70
Maximum	112.0	245.1	2.70	0.0462	0.0203	9.20	177.33	10.00
Minimum	55.3	57.2	-3.84	-0.0669	-0.0440	-0.01	-284.86	3.80
Std. Dev.	11.9	32.0	0.50	0.0080	0.0062	2.65	46.63	1.46
Skewness	-0.47	0.98	-1.75	-1.19	-1.68	0.03	-0.90	0.84
Kurtosis	2.88	3.80	19.74	24.96	12.44	1.78	8.27	3.09

Panel B: Summary Statistics for Europe

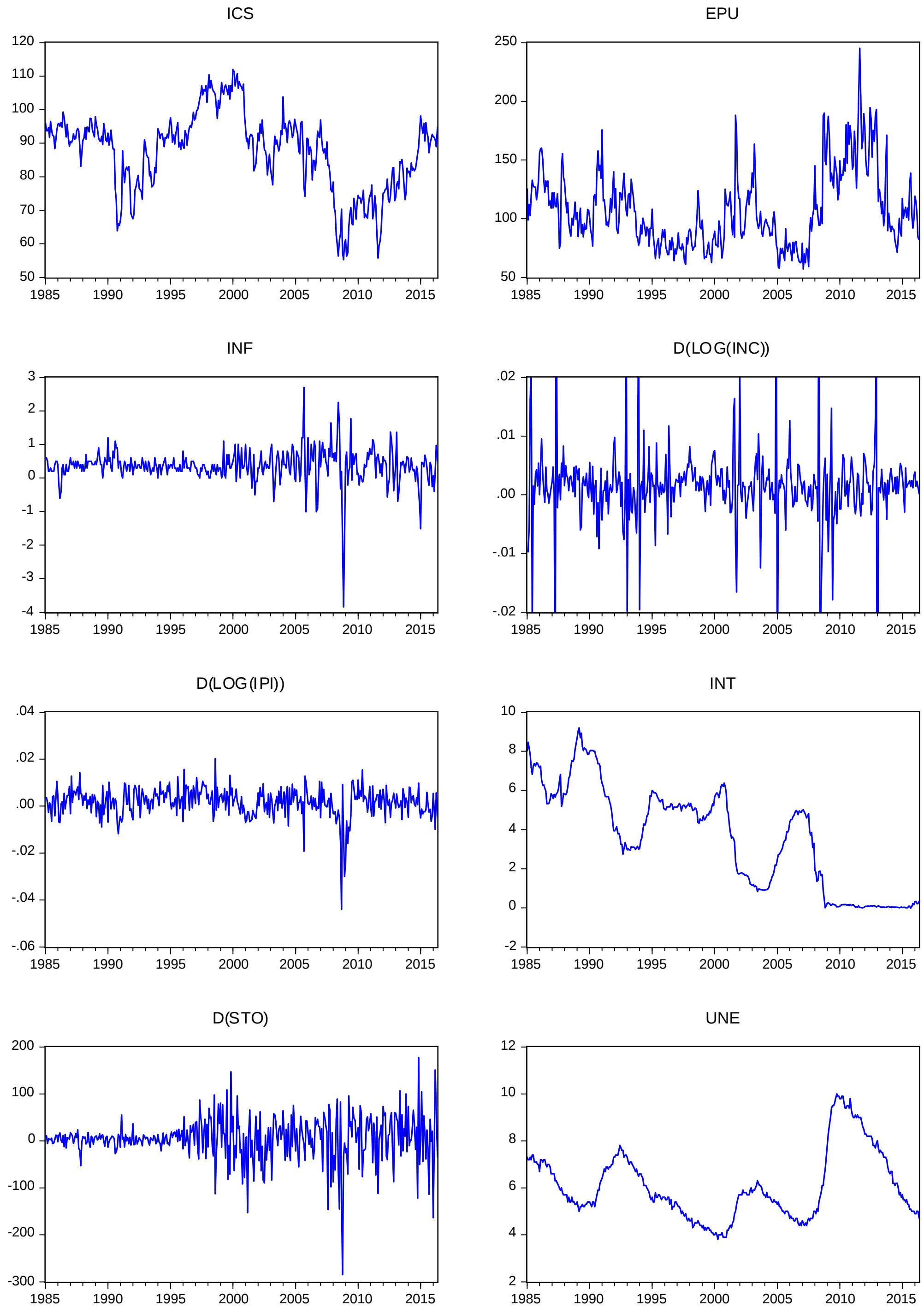
	CCI	EPU	INF	$\Delta\log(\text{INC})$	$\Delta\log(\text{IPI})$	INT	ΔSTO	UNE
Mean	-11.9	122.1	0.13	0.0010	0.0006	3.73	5.97	9.71
Median	-11.6	108.4	0.14	0.0010	0.0012	3.36	15.02	9.90
Maximum	1.6	304.6	1.27	0.0280	0.0238	11.82	451.03	12.10
Minimum	-32.5	47.7	-1.54	-0.0126	-0.0415	-0.25	-396.49	7.20
Std. Dev.	7.2	48.7	0.33	0.0027	0.0096	2.99	114.41	1.27
Skewness	-0.47	0.96	-0.79	2.37	-0.72	0.88	-0.41	-0.11
Kurtosis	2.81	3.43	8.85	42.92	5.26	3.19	4.72	1.99

Note: Refer to Table 2.4 for variable notation.

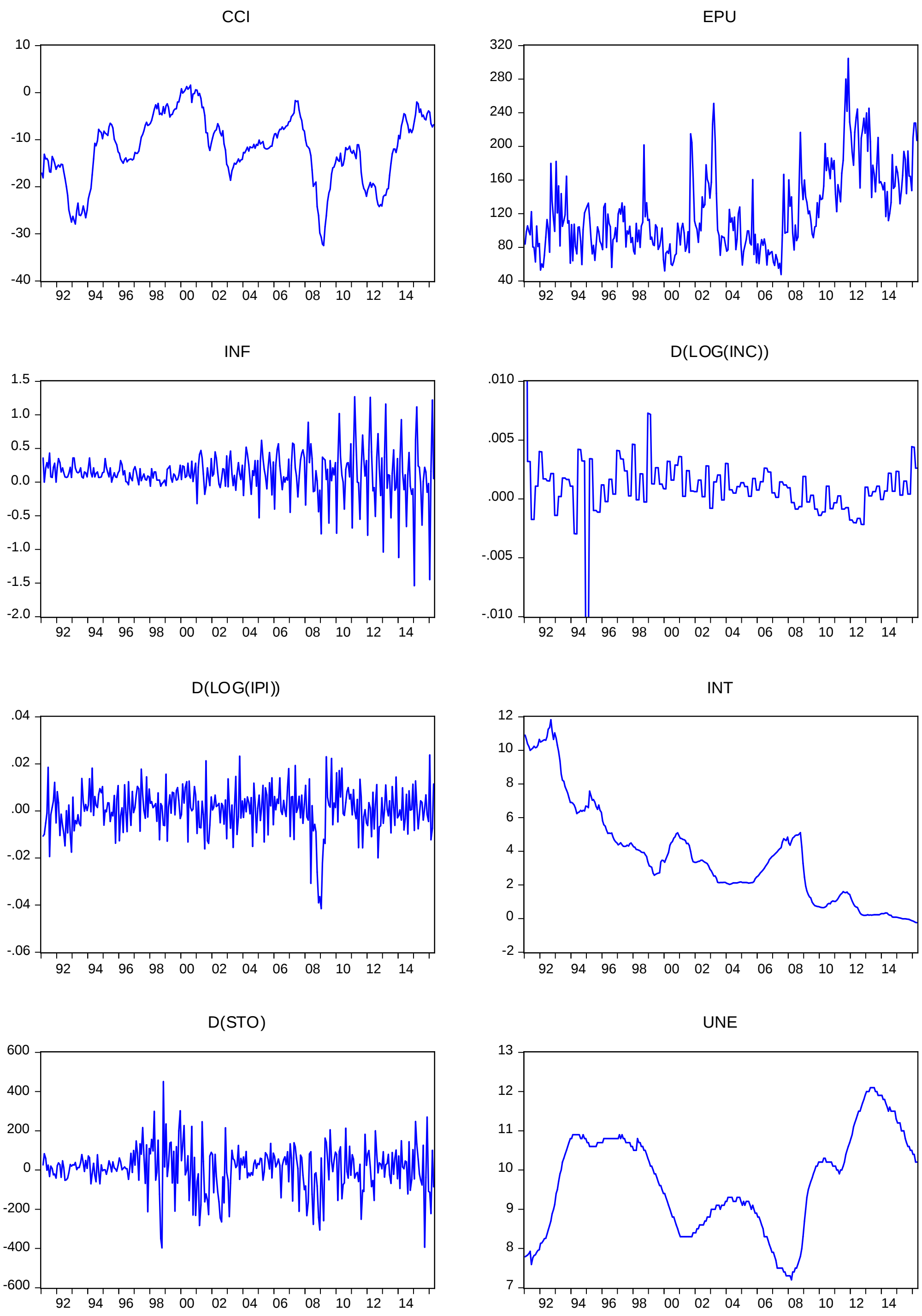
For the main variable ICS, we can observe from Figure 2.2 that it dropped sharply in around 1990 (due to Gulf War) and from 2007 to 2009 (due to the Global Financial Crisis). Among the sharp drops, the most recent Global Financial Crisis seems to have the largest and the most prolonged impact. ICS reached its historical low in November 2008 (at value 55.3) after over a year's almost monotonic decrease. Around the same time, economic variables such as IPI and STO also suffered from large drops. ΔIPI reached its historical low in September 2008, and ΔSTO, in October 2008. Apparently, we should be able to explain the low value of ICS in November 2008 by economic variables such as $\Delta\log(\text{IPI})$ and ΔSTO.

Figure 2.2
Time Series for all the Variables

(a) Time Series for US



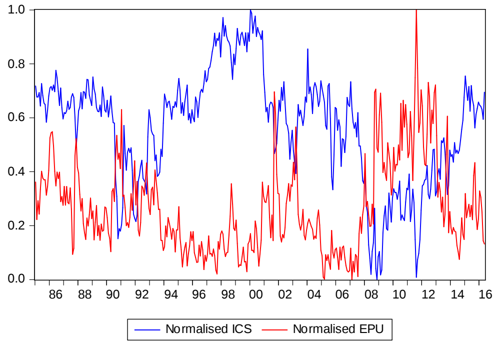
(b) Time Series for Europe



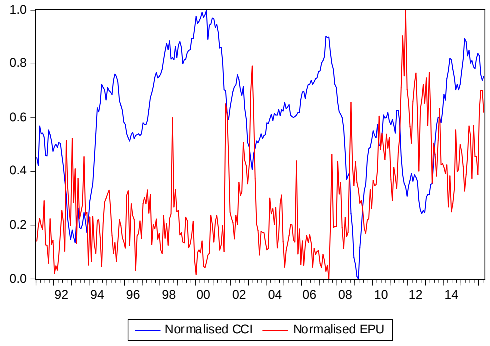
Note: Refer to Table 2.4 for variable notation.

Figure 2.3
Time Series for Main Variables

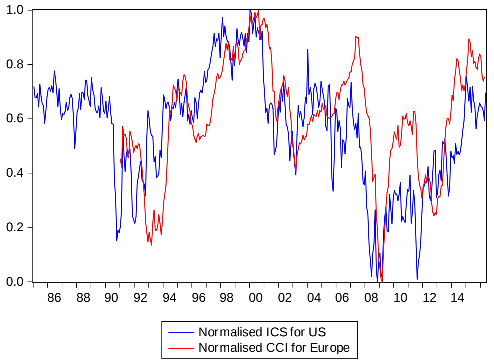
(a) Normalised ICS and EPU for US



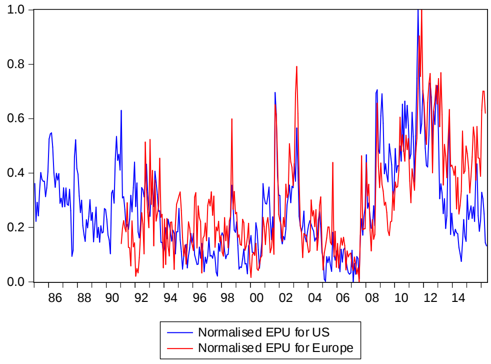
(b) Normalised ICS and EPU for Europe



(c) Normalised ICS/CCI for US and Europe



(d) Normalised EPUs for US and Europe



The recovery of ICS is also quite slow, which takes more than five years. Interestingly, ICS dropped again to a nearly historical low value in August 2011 (at value 55.8), when the Great Recession was already officially ended (according to NBER's Business Cycle Dating Committee, the Great Recession started in December 2007, and ended in June 2009). This shows that consumers were as pessimistic about the US economy as they were in the middle of the Great Recession. Unlike the September 2008 case, we do not find STO and IPI to decrease rapidly around August 2011. Therefore, we can no longer explain the extremely low value of ICS in November 2008 by economic variables such as $\Delta \log(\text{IPI})$ and ΔSTO. Instead, among the time series of all the variables, we find that EPU reached its historical high in August 2011, which makes it a very useful candidate as an explanatory variable for ICS.

To visualise the relationship between ICS and EPU, we rescaled their values linearly to [0, 1] (let $\hat{y} = \frac{y - \min(y)}{\max(y) - \min(y)}$), and plot them in the same graph (Figure 2.3 (a)). Apparently, they tend to move in opposite directions. A large swing in ICS often corresponds to a large swing (in the opposite direction) in EPU, and sometimes, the latter leads the former slightly (for example, a local high in EPU in September 1998 corresponds to a local low in ICS in October 1998).

The summary statistics of the European data are reported in Table 2.5 (Panel B). The values of CCI are not directly compatible to ICS in the US due to different benchmarks and calculation methods. Concerning the range of CCI, the possible values it can take ranges from -100 (100% strong unfavourable answers) to 100 (100% strong favourable answers), with neutral value 0 (same percentage of favourable and unfavourable answers). The actual index ranges from -32.5 to 1.6, with average -11.9. Unlike ICS for US, CCI for Europe is below the neural value most of the time, and has lower variance. When we check the answers to the individual questions, it can be confirmed that more people chose "slightly negative" and "very negative" answers than positive ones most of the time (except for Q4, where more people expect a saving). This implies that on average, the European consumers might be more pessimal about the economic and buying conditions than US consumers. We also checked the country specific answers, and found that the results differ from countries. For example, CCI of Denmark is much higher (with average 5.7) than CCI of Greece (with average -37). The diverse results were also discussed in Lemmens et al. (2007). The Skewness and Kurtosis of ICS and CCI are quite similar. In Figure 2.3 (c), we rescaled European CCI and US ICS to [0, 1], and plotted the two time series on the same graph. Interestingly, it clearly shows the similarity of the two series, and CCI for Europe tends to change in the same direction as ICS for US (sometimes with a small lag). The similarity of the two time series shows that although European consumers are generally more pessimal than US consumers, the change in their confidence still provides similar information to the change in US consumers' confidence.

On the other hand, EPU for Europe ranges from 47.7 to 304.6, with average 122.1. It has higher average and variance than the EPU for US. In other words, the uncertainty level in economic policy tends to be higher in Europe than in the US. The Skewness and Kurtosis are similar to that of US data. After rescaling the EPU time series for both areas and plotting them together (In Figure 2.3 (c)), we can clearly see that these two time series tends to move in same directions, and unlike ICS/CCI, there are no obvious lags between the movements for US and Europe. Figure 2.3 (b) plotted the rescaled European CCI and EPU together. Similar to the US data, they tend to move in opposite directions. However, the relationship is not as clear as the US one shown in Figure 2.3 (a).

Finally, from Figure 2.2, we may notice some similarities in EPU and UNE. It is quite intuitive, because both higher EPU and higher unemployment rate are likely to be associated with worse economy. However, EPU is much more fluctuated, and the distinctions are clear. Therefore, it is interesting to study the additional explanatory power of EPU on ICS/CCI controlling for UNE.

2.3 Methodology

Our objective is to test the hypothesis about the relationship between economic policy uncertainty and consumer confidence: higher EPU leads to lower ICS. In the Data Section, we already found some evidence. In this section, we explain the complete data analysis procedure we shall take in search for the empirical evidence, which includes calculation of correlation, regression analysis, and Vector Autoregression (VAR) model analysis. Under the VAR model, we performed granger causality tests, impulse response analysis, and variance decomposition. Our choices of approaches were based on the characteristics of the data and the existing literature.

2.3.1 Correlation

We first calculate the correlation matrix for all the variables. We are especially interested in the correlation between two main variables corr(y, x), where y is a consumer confidence measure and x is an economic policy uncertainty measure. At this stage, y=ICS/CCI, and x=EPU. Based on our hypothesis, we expect their correlation to be large and significantly negative.

The correlation does not tell us how well several lags of EPUs can explain ICS/CCI, nor can it tell us the extra explanatory power of EPU on ICS/CCI given control variables. Therefore, we move to a regression model.

2.3.2 Regression Model

We then focus on the following regression model in Equation 2.3.1. In the equation, t denotes the time period (monthly), and T^* denotes the optimal number of lags according to Akaike information criterion (with maximal number of lags for consideration being 10). Z denotes the controlled variable vector, {INF, Δ(log(INC)), Δ(log(IPI)), INT, ΔSTO, and UNE}. Again, at this stage, dependent variable y=ICS/CCI, and the main variable x=EPU.

$$\mathrm{y}_t = \alpha + \sum_{i=1}^{T^*} \beta_i \mathrm{x}_{t-i} + \gamma Z_{t-1} + \epsilon \tag{2.3.1}$$

We are interested in the sign of the coefficients of the lagged values of EPU, or $\sum_{i=1}^{T^*} \beta_i$. We expect it to be negative and significant. We are also interested in the (extra) explanatory power of EPU. To do this, we further consider the following two regression equations:

$$\begin{aligned} \mathrm{y}_t &= \alpha + \gamma Z_{t-1} + \epsilon & (2.3.2) \\ \mathrm{y}_t &= \alpha + \sum_{i=1}^{T^*} \beta_i \mathrm{x}_{t-i} + \epsilon & (2.3.3) \end{aligned}$$

We will calculate the change in adj-R^2 from Model 2.3.2 to Model 2.3.1, and this value shows the extra explanatory power of EPU on ICS/CCI. We will also record adj-R^2 of Model 2.3.3, which implies how much variance of ICS/CCI can EPU alone explain.

The regression models help us test our hypothesis in several angles. However, there are several limitations: firstly, they suffer from autocorrelation problem. Secondly, they do not tell us whether the relationship is causal. Thirdly, they do not allow us to check when there is a shock in EPU, how ICS/CCI would respond to it. These limitations can be overcome by a vector autoregression model. Therefore, we proceed to the vector autoregression model.

2.3.3 Vector Autoregression (VAR) Model

Our VAR model is similar to the regression model. We regard all variables (a consumer confidence measure, an economic policy uncertainty measure, and six other variables) as endogenous variables. The model has the following format:

$$Y_t = A_0 + \sum_{i=1}^{T^*} A_i Y_{t-i} + u_t,$$

where Y_t denotes the endogenous variable vector, u_t denotes the error vector that satisfies certain criteria, A_i denotes the coefficient vector, and T^* denotes the optimal number of lags. In particular, we consider the following three models: Model (1): $Y = \{y, x, Z\}$, where Z is defined in the regression model. Model (2): $Y = \{y, Z\}$. And Model (3): $Y = \{y, x\}$. Again, at this stage, $y =$ICS/CCI, and $x =$EPU.

Please note that since there is not enough knowledge and theory to suggest restrictions to orthogonalizes the errors, we are not setting up a structural VAR model. Using the reduced form VAR model is a common approach in literature

(Barsky and Sims, 2012). We can still interpret results such as impulse response functions in terms of the displacement of forecasts implied by unexpected movements in the variables. Because once we know the reduced-form shocks and how they have affected today's value of the variables, we can use the reduced-form coefficients to forecast.

Under the VAR model, we first record coefficient and adj-R^2 values just as in the regression model.

Once we have estimated a VAR model, we are also able to analyse its properties using structural analysis, which includes three interdependent approaches. The first approach is the Granger causality test. We do both pairwise Granger causality test between the main variables, and Granger causality test for the complete model (with control variables). In particular, to test whether EPU pairwise Granger causes ICS/CCI, we consider the following model:

$$y_t = a_0(1) + \sum_{i=1}^{T^*} a_i(1,1)y_{t-i} + \sum_{i=1}^{T^*} a_i(1,2)x_{t-i} + u_t(1). \tag{2.3.4}$$

And to test whether EPU Granger causes ICS/CCI in the complete model, we consider the following model:

$$y_t = a_0(1) + \sum_{i=1}^{T^*} a_i(1,1)y_{t-i} + \sum_{i=1}^{T^*} a_i(1,2)x_{t-i} + \sum_{i=1}^{T^*} B_i(1)Z_{t-i} + u_t(1). \tag{2.3.5}$$

In both cases, we test the joint hypothesis:

$$a_1(1,2) = a_2(1,2) = ... = a_{T^*}(1,2) = 0,$$

with Null hypothesis being x does not Granger cause y.

Secondly, under the VAR model, we also obtain the impulse response functions (IRF). The IRF gives the jth-period response when the system is shocked by a one-standard-deviation shock. We are interested in tracing the dynamics of ICS/CCI to a shock to EPU. We expect that a shock to EPU causes ICS/CCI to change negatively temporarily.

Finally, we perform variance decomposition. While impulse response functions trace the effects of a shock to one endogenous variable on to the other variables in the VAR, variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR. Thus, the variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR. In particular, we focus on the decomposition of ICS/CCI. The variance decomposition results tell us in the short run (for example, at the 2nd month) and in the long run (say, in 60 months, or 5 years), shock to EPU accounts for how much variation of the fluctuation in ICS/CCI. We expect that part of the variance of ICS/CCI is explained by EPU.

2.4 Results and Discussions

2.4.1 Correlation

Table 2.6 presents the correlations among all variables used in our study. For the US, the correlation between ICS and EPU is -0.628 (with $p-$value 0.0000). For Europe, the correlation between CCI and EPU is -0.336 (with $p-$value 0.0000). From the results, we can make two observations: (1), the correlations between ICS/CCI and EPU are negative and significant. And (2), $|\text{corr}(\text{ICS}_{\text{us}}, \text{EPU}_{\text{us}})| >> |\text{corr}(\text{CCI}_{\text{eu}}, \text{EPU}_{\text{eu}})|$.

The first observation implies that when EPU increases, ICS/CCI tends to decrease. It is consistent with our hypothesis. Here we provide **two possible explanations** for the negative correlation:

1. EPU reflects current economic conditions (for example, the government may be more uncertain about its economic policy making when unemployment rate is higher and the business condition is worse), and the current economic conditions influence consumer confidence.

2. As we discussed in Introduction and Literature Review sections, EPU causes consumer uncertainty, and consumer confidence measures uncertainty.

Table 2.6
Correlation Matrices

Panel A: Correlation Matrix for US

Correlation	ICS	EPU	INF	$\Delta\log$(INC)	$\Delta\log$(IPI)	INT	ΔSTO	UNE
ICS	1							
EPU	-0.628	1						
INF	-0.008	-0.101	1					
$\Delta\log$(INC)	0.120	-0.083	-0.158	1				
Δ(log(IPI))	0.236	-0.201	0.061	0.073	1			
INT	0.501	-0.372	0.108	0.036	0.100	1		
ΔSTO	0.100	-0.154	0.074	0.068	0.008	-0.011	1	
UNE	-0.683	0.681	-0.057	-0.066	0.007	-0.462	0.054	1

Panel B: Correlation Matrix for Europe

Correlation	CCI	EPU	INF	$\Delta\log$(INC)	$\Delta\log$(IPI)	INT	ΔSTO	UNE
CCI	1							
EPU	-0.336	1						
INF	-0.032	-0.029	1					
$\Delta\log$(INC)	0.180	-0.210	-0.064	1				
Δ(log(IPI))	0.258	-0.113	0.005	0.001	1			
INT	-0.180	-0.445	0.077	0.130	-0.106	1		
ΔSTO	0.048	-0.171	0.053	0.054	0.172	-0.026	1	
UNE	-0.111	0.408	-0.096	-0.151	0.128	-0.406	0.154	1

Note: Refer to Table 2.4 for variable notation.

The first explanation implies that although EPU and ICS/CCI may be highly correlated, the information in EPU may already be embedded in other economic variables (such as unemployment rate, IPI, stock market index, etc). On the other hand, the second explanation implies that EPU affects consumer confidence through a new channel, and even other economic variables are included in the model, EPU should still have some additional explanatory power.

There are several approaches that can be used to prove which explanation is closer to reality. The first approach is to study the regression model. By adding economic and financial variables as control variables, we are able to check the additional explanatory power of EPU.

The second approach is to decompose consumer confidence to the current component and the expected component. Study the relationship between EPU and the consumer confidence components. If it is more closely linked with the current component, the first explanation works better. Otherwise, the second explanation makes more sense. We will do it as the first additional test, and discuss the results in Additional Analyses Section.

Finally, we can study the relationship between EPU and the percentage of consumers who choose the "unsure" answers in the consumer confidence surveys. The goal is to check the validity of the second part of explanation two, i.e., consumer confidence measures uncertainty, or in other words, more uncertainty implies lower confidence. In particular, we want to find out whether EPU leads to higher "unsure" rate, and hence more neutral consumer confidence, or as the second explanation claims, EPU leads to more "negative" answers, and hence lower consumer confidence. This will be the second additional test we do, and the results will be discussed in Additional Analyses Section.

The second observation (i.e., the correlation of EPU and Consumer Confidence is much higher in the US than in Europe) also has a few possible explanations and research methods. For example, since different from ICS for US, CCI for Europe is forward looking only, maybe EPU is indeed less correlated with the expected component of Consumer Confidence. We can make use of the $\text{ICS}_{\text{equiv}}$ we constructed for Europe, and study the relationship between decomposed consumer confidence components and EPU in the first additional test.

Secondly, since EPU for US contains four components, but EPU for Europe is only news based, the difference in correlation may imply the EPU for US is more effective. To prove whether this is the case, we study the relationship between decomposed EPU components and consumer confidence in the third additional test in Additional Analyses Section.

The third possible explanation is that since US is the largest economy in the world, the European CCI may be influenced more by US variables, and less by its own EPU and economic variables. The transaction/spillover problem is quite interesting, and will be studied in a separate chapter.

Another difference is that the European variables are weighted averages of country specific data. Lemmens et al. (2007) found that the consumer confidences among different European countries are quite diverse. Therefore, the aggregated index may suffer from lower correlation with aggregated EPU. However, it still makes sense to regard Europe as one region, so that it is more comparable with the US. In fact, we have tried to study the country-specific relationships between EPU and CCI, and the results are mixed up.

2.4.2 Regression

The regression results are summarised in Table 2.7. The regression results show that for the US, $\sum_{i=1}^{T^*} \beta_i$ in Model 2.3.1 is -0.068 (obtained at $T^* = 1$), and it is significant at 1% level. According to the regression equation, when EPU increases by 10, ICS decreases by 0.68. Adj-R^2 of Models 2.3.1 and 2.3.2 are 0.597 and 0.582, respectively. By adding one explanatory variable EPU, adj-R^2 increases by 2.6%. EPU alone is able to generate adj-R^2 of 0.406 (obtained at $T^* = 3$). These results imply that EPU alone can explain ICS quite well. However, taking other control variables into account, EPU only has a small additional explanatory power on ICS.

On the other hand, for the Europe, $\sum_{i=1}^{T^*} \beta_i$ in Model 2.3.1 is -0.124 ($T^* = 6$). According to the regression equation, when EPU increases by 10, ICS decreases by 1.24. Adj-R^2 of Models 2.3.1 and 2.3.2 are 0.437 and 0.173, respectively. By adding one explanatory variable EPU, adj-R^2 increases by 153%. EPU alone is able to generate adj-R^2 of 0.144 ($T^* = 2$). Comparing with the US result, the European results show that although EPU alone has a lower explanatory power on CCI, the control variables also have a much lower explanatory power, and EPU has a much larger additional explanatory power when both EPU and control variables are included in the model. In other words, EPU influences CCI through a channel different from other economic variables.

The other interesting observation is that the optimal number of lags of EPU in the regression model is much bigger for Europe than for the US. The result is compatible with our observations from the plots of these time series. While the EPU values from the two areas tend to move in the same direction at the same time, the CCI values for Europe tend to move in the same direction with the ICS for US, but with a few months of delays. This means that if it is the best to explain ICS by EPU with one lag for the US, it might be the best to explain CCI by EPU with several lags for Europe. In other words, the results and plots imply that for Europe, the movements in EPU tend to lead the movements in CCI for a longer period (a few months).

Based on the regression results, it seems that the first explanation discussed in the previous section (i.e., EPU reflects current economic conditions) seems to work better for the US, and the second explanation (i.e., EPU causes consumer uncertainty) seems to work better for Europe. However, we still need more evidence from the VAR causality test and the additional tests we discussed before to better understand the relationship between EPU and ICS/CCI. In particular, for the US, the similarity between the two time series, EPU and UNE (unemployment rate), may be the reason for the low additional explanatory power of EPU. Therefore, it is important to compare the causality results among EPU, UNE, and ICS, to understand the dynamics among these variables.

2.4.3 VAR Model

The results from the VAR models are summarised in Table 4.4. Since lagged ICS/CCI values are added, R^2 is quite high for all the models, and the additional explanatory power by adding EPU is small. However, the results still confirm a neg-

Table 2.7
Influence of EPU on ICS/CCI from Regression Results

	With EPU only (3)			With Z only (2)	With EPU and Z (1)			Incremental [(1)-(2)]
	Adj-R^2	$\sum \beta_i$	p	Adj-R^2	Adj-R^2	$\sum \beta_i$	p	Adj-R^2
US	0.406	-0.253	0.000	0.582	0.597	-0.068	0.000	0.015 (2.6%)
Europe	0.144	-0.060	0.000	0.173	0.437	-0.124	0.000	0.163 (153%)

Note: Models (1) - (3) are as follows, respectively:
$\text{ICS/CCI}_t = \alpha + \sum_{i=1}^{T^*} \beta_i \text{EPU}_{t-i} + \sum_{i=1}^{T^*} \gamma_i Z_{t-i} + \epsilon$
$\text{ICS/CCI}_t = \alpha + \sum_{i=1}^{T^*} \gamma_i Z_{t-i} + \epsilon$
$\text{ICS/CCI}_t = \alpha + \sum_{i=1}^{T^*} \beta_i \text{EPU}_{t-i} + \epsilon$
Here, T^* is chosen by Akaike information criterion. For US, $T^* = 1$ for model (1) and $T^* = 3$ for model (3), and for Europe, $T^* = 6$ for model (1), and $T^* = 2$ for model (3).
$Z = \{\Delta \log(\text{INC}), \Delta \log(\text{IPI}), \text{INT}, \Delta(\text{STO}), \text{UNE}\}$. Refer to Table 2.4 for variable notation.

ative relationship with ICS/CCI (i.e., negative $\sum \beta_i$ values) and a small additional explanatory power. The results are consistent with our expectations. For US and Europe, the optimal numbers of lags according to Akaike information criterion are 2 and 7, respectively. The optimal number of lags is much bigger for Europe than for the US, similar to the regression results, and the reason was already discussed in the previous section. In the subsections, we interpret the VAR model by three approaches, which can not be done in the regression model.

Table 2.8
Influence of EPU on ICS/CCI from VAR Results

	With EPU only			With Z only	With EPU and Z			Incremental
	Adj-R^2 (3)	$\sum \beta_i$	p	Adj-R^2 (2)	Adj-R^2 (1)	$\sum \beta_i$	p	Adj-R^2 [(1)-(2)]
US	0.900	-0.004	–	0.906	0.908	-0.007	–	0.003
Europe	0.969	0.0004	–	0.973	0.975	-0.008	–	0.002

Note: Models (1) - (3) have the following form:
$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_{T^*} y_{t-T^*} + e_t$
For Model (1), $y = \{ICS, EPU, Z\}$, where Z is defined in Table 2.7.
For Model (2), $y = \{ICS, Z\}$. For Model (3), $y = \{ICS, EPU\}$.
Here, T^* is the optimal number of lags chosen by Akaike information criterion. For US, $T^* = 2$ for model (1) and $T^* = 3$ for model (3), and for Europe, $T^* = 7$ for model (1), and $T^* = 7$ for model (3).

Granger Causality

The Granger Causality results are summarised in Table 2.9. It shows that at test critical value 5%, both pairwise or within the complete model, for the US, EPU Granger causes ICS, but ICS does not Granger cause EPU. And for Europe, EPU and CCI Granger cause each other. The reason why CCI Granger causes EPU for Europe might be that the optimal length of lags is too big (7 months), and the joint hypothesis for Granger causality test is too tight. From these results, we conclude that for US and European Data, EPU Granger causes ICS/CCI, and ICS/CCI normally does not Granger cause EPU. This implies that the lagged values of EPUs have extra explanatory power on ICS/CCI, given its own lagged values, but not the other way around. The result is consistent with our hypothesis. The change in EPU leads the change in consumer confidence. On the one hand, EPU may imply the current business condition, which may cause change in consumer confidence. On the other hand, EPU may cause consumer uncertainty, which may change consumer confidence. In contrast, consumer confidence might also lead EPU. Consumer confidence implies consumers' buying intention, and hence may cause the government's uncertainty on economic policy. However, this part is not quite supported by the empirical results.

Previously, from the regression result, we pointed out that for the US, the limited additional explanatory power of EPU on ICS may due to the similarity between EPU and unemployment rate UNE. Here, we compared their Granger causality results in Table 2.9 Panel C. The results show that UNE does not Granger cause ICS. And for the complete model, although UNE Granger causes ICS, ICS also Granger causes UNE. Compared wth EPU, UNE does not seem to lead ICS as EPU does. Therefore, EPU seems to have its unique advantage in explaining ICS. Moreover, it implies that EPU affects ICS through a different channel rather than just implying current economic conditions. In other words, the results show some support on our second explanation discussed in the correlation result section.

Table 2.9
Granger Causality Results

Panel A: Pairwise Granger Causality

Null Hypothesis:	F-Statistic	Prob.
For US:		
EPU does not Granger Cause ICS	7.71	0.0000
ICS does not Granger Cause EPU	2.55	0.055
For Europe:		
EPU does not Granger Cause CCI	2.89	0.0063
CCI does not Granger Cause EPU	3.38	0.0017

Panel B: Granger Causality for the Complete VAR Model

Dependent Variable	Excluded	Chi-sq	Prob.
For US:			
ICS	EPU	10.4	0.0056
EPU	ICS	1.41	0.4931
For Europe:			
CCI	EPU	25.4	0.0006
EPU	CCI	14.7	0.0401

Panel C: Granger Causality between UNE and ICS for US

Pairwise:

Null Hypothesis:	F-Statistic	Prob.
For Europe:		
UNE does not Granger Cause ICS	1.99	0.1149
ICS does not Granger Cause EPU	12.0	0.0000

Complete Model:

Dependent Variable	Excluded	Chi-sq	Prob.
ICS	UNE	20.1	0.0000
UNE	ICS	78.2	0.0000

Note: for Panel A, optimal number of lags from model (3) is used. In particular, $T^* = 3$ for US and $T^* = 7$ for Europe. For Panels B and C, optimal number of lags from model (1) is used. $T^* = 2$ for US, and $T^* = 7$ for Europe.

Impulse Response Functions

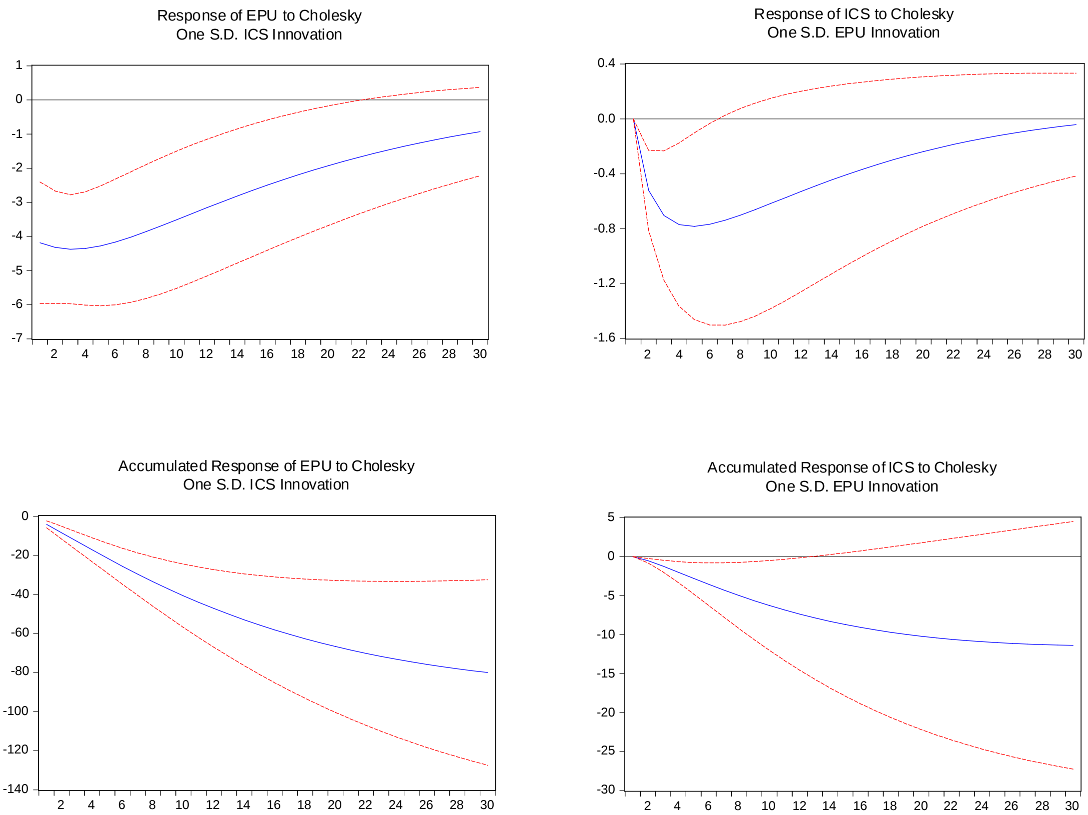
Figure 2.4 (a) shows the impulse responses between EPU and ICS in the US. When there is a one standard-deviation shock in ICS, EPU has a negative response immediately, and the shock was absorbed slowly. Cumulatively, it has a negative impact. On the other hand, when there is a shock in EPU, ICS has a negative response in the second month, and then the shock was completely absorbed in the 4th month. Cumulatively, it has a significantly negative impact in the short run, but an insignificant negative impact in the long run.

Figure 2.4 (b) shows the impulse responses between EPU and CCI in the Europe. When there is a one standard-deviation shock in CCI, EPU has a negative response immediately, and the shock was absorbed within a few months. Cumulatively, it has a negative impact. On the other hand, when there is a shock in EPU, CCI has a negative response in the second month, and then the shock was completely absorbed slowly. Cumulatively, it also has a significantly negative impact in the short run, but an insignificant negative impact in the long run. Although the time used to absorb the shocks is somewhat different for Europe and US, the trends of the impulse responses for US and Europe are very similar. Both show that EPU and ICS/CCI have a negative relationship, and EPU seems to lead ICS/CCI, which are consistent with our hypothesis and the previous results.

The shock in EPU takes longer to be absorbed by CCI for Europe than for US, probably because the number of lags is much larger for Europe ($T^* = 7$) than for US ($T^* = 2$). It is also quite interesting that the accumulative impulse responses of ICS/CCI by one standard-deviation shock in EPU are insignificant in accumulatively, for both areas. This is actually quite intuitive. The uncertainty on economic policies implied by EPU can be resolved when new policies are proposed or announced, and this assumption is shared by all the customers. Therefore, it does not affect consumer confidence under accumulated short-run effects. The impact of shocks in the short run and the long run can be further analysed by variance decomposition, which is discussed in the next section.

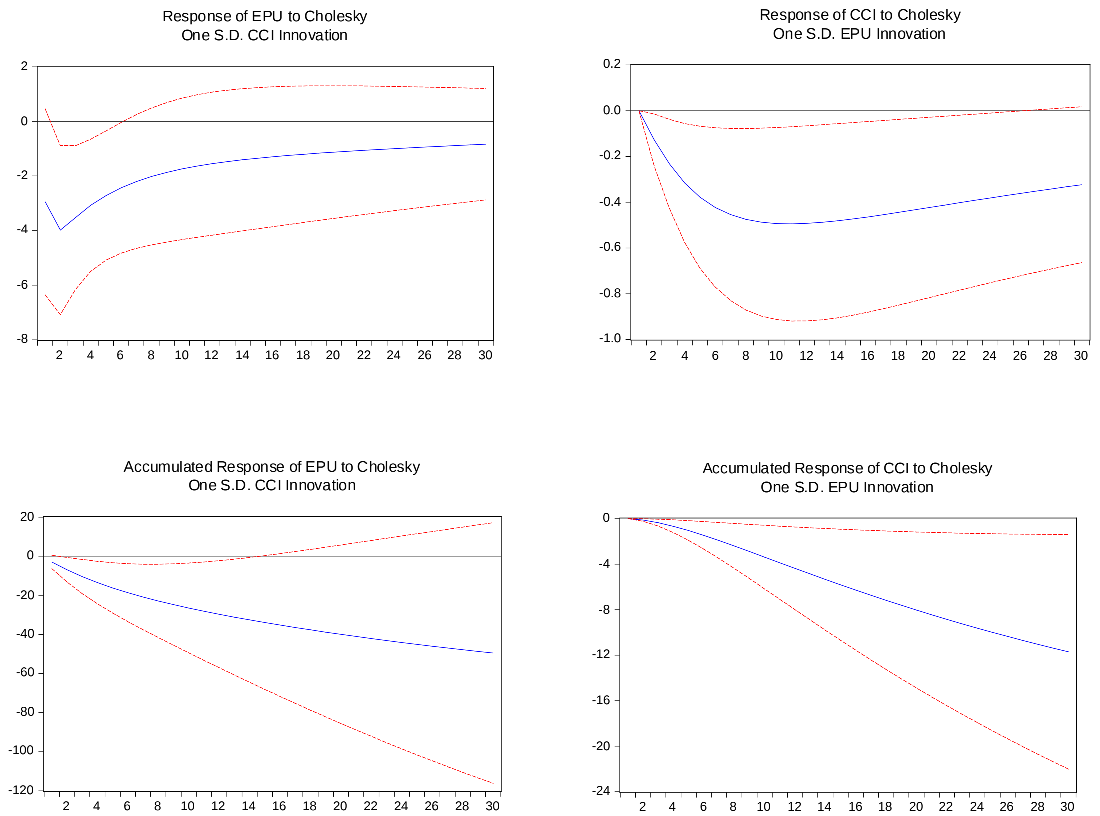
Figure 2.4
Impulse Response Results

(a) Impulse Response Results for US



Note: optimal # of lags = 2.

(b) Impulse Response Results for Europe



Note: optimal # of lags = 7.

Variance Decomposition

Table 2.10 shows the variance decomposition results. For the US, in the short run (i.e., at the second month), a shock in EPU explains about 2.66% of the variance in ICS, largest among all the variables except for ICS itself. In the long run (i.e., after 5 years, or 60 months), a shock in EPU explains about 1.97% of the variance in ICS. Meanwhile, ICS's own shock still accounts for 77.93% of its variance. Among all the other variables, a shock in $\Delta \log(\text{IPI})$ causes the largest fluctuation in ICS, 11.53%. On the other hand, for Europe, EPU explains about 3.93% of the variance in CCI in the short run, also the largest among all the variables except for CCI itself. In the long run, EPU explains as large as 15.19% of the variance in CCI. A shock in CCI itself only accounts for 27.61% of its long run fluctuation, and many variables make significant contributions to the variance in CCI.

The difference between the findings for US and Europe is partially due to the difference in the optimal number of lags. By adding more lags to the model, variables are linked with each other in more dimensions. But still, it implies that for Europe, a shock in EPU can explain the variance in CCI much better than for US, especially in the long run. In other words, European's EPU is more useful in determining its consumer confidence. This finding is consistent with the regression results. To find the reasons behind it, we will proceed to the additional analyses section.

Please note that the results are sensitive to variable ordering. And also, we should use a structured VAR model to providing more meaningful results. Nonetheless, the results provide us with some insights and grounds for comparison. And a more solid discussion can be done in the future when the structured VAR is constructed.

Table 2.10
Variance Decomposition Results of ICS/CCI

Panel A: Variance Decomposition Results for US

Period	S.E.	ICS	EPU	INF	$\Delta\log(\text{INC})$	$\Delta\log(\text{IPI})$	INT	ΔSTO	UNE
1	3.61	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	5.09	92.26	2.66	1.50	0.03	1.48	0.98	0.96	0.15
3	6.15	88.15	2.45	1.62	0.04	3.78	1.39	2.12	0.44
...					......				
60	12.19	77.93	1.97	0.75	0.02	11.53	2.14	3.95	1.70

Panel B: Variance Decomposition Results for Europe

Period	S.E.	CCI	EPU	INF	$\Delta\log(\text{INC})$	$\Delta\log(\text{IPI})$	INT	ΔSTO	UNE
1	1.14	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	1.72	93.87	3.93	0.70	0.00	0.31	0.24	0.36	0.59
3	2.21	89.07	5.58	0.52	0.11	1.20	0.51	0.89	2.11
...					......				
60	7.28	27.61	15.19	18.37	8.97	10.36	6.18	0.65	12.68

Note: Cholesky Ordering: ICS/CCI EPU INF $\Delta\log(\text{INC})$ $\Delta\log(\text{IPI})$ INT ΔSTO UNE. Refer to Table 2.4 for variable notation.

2.4.4 Summary and Discussions

Our results show that for the US, EPU and ICS have a large negative correlation. The regression results show that EPU has a small negative (and significant) additional explanatory power in ICS, controlling for other economic variables. From the VAR model, EPU Granger causes ICS, but not the other way around. The impulse response results also show that EPU seems to lead ICS. And the variance decomposition results confirm the small explanatory power of EPU in ICS. Overall, the results imply that EPU is closely linked with ICS. They often move in opposite directions. However, other variables can explain most changes in EPU, and therefore, the extra explanatory power of EPU is not that large. Nonetheless, unlike other variables, the change in EPU tends to lead the change in ICS, which makes it useful in the model, and also implies that EPU affects ICS through a different channel rather than simply implying current business conditions. In summary, the results imply that EPU affects ICS in two channels. Firstly, EPU implies information also contained in control variables. And the control variables can explain ICS quite well. Therefore, EPU alone can explain ICS well, but adding the control variables, it only has a small additional explanatory power. But more importantly, EPU also leads to consumer uncertainty. And consumer uncertainty is part of consumer confidence. Therefore, EPU tends to lead ICS, and other control variables.

For Europe, EPU and CCI have a negative correlation, but smaller than that for US. The regression results show that EPU has a large negative (and significant) additional explanatory power in CCI, controlling for other economic variables. From the VAR model, EPU Granger causes ICS. The impulse response results also show that EPU seems to lead CCI. And the variance decomposition results confirm a large extra explanatory power of EPU in CCI. Overall, the results imply that compared to other control variables, EPU is closely linked with CCI, by moving in opposite directions. The results imply that EPU mainly affects CCI through the second channel we discussed in the previous paragraph, namely, EPU leads to consumer uncertainty. And consumer uncertainty is part of consumer confidence. Therefore, EPU tends to lead CCI, and explain CCI in the way that the control variables cannot. Moreover, we have discussed the reasons why the control variables can not explain CCI well. One possibility is that CCI in Europe is affected by the variables in US. This will be studied in a future chapter.

The other possible reasons include the validity of EPU and CCI. For example, the EPU for US has four components, but the EPU for Europe is only news based. Moreover, ICS for US is calculated from survey results that contain two current situation questions and three forward looking questions, but CCI for Europe is based on four forward looking questions only. Furthermore, the designs of questions and choices are different. Therefore, in the next section, we try to find our answers through several detailed decomposed data analysis approaches.

We have suggested two channels through which EPU determines ICS/CCI. One thing that may need further explanation is: why control variables can explain ICS/CCI, and in what aspect does EPU impact consumer uncertainty? To answer this question, we further studied the relationship between categorised EPUs and ICS, and compared the results with the one between categorised EPUs and producer confidence. The results are also discussed in the next section.

2.5 Additional Analyses

In the previous section, we focused on the empirical evidence on the effect of EPU on ICS/CCI. While the main research question has been addressed, we can still dig into the data in order to better understand the relationship between the two variables. In this section, we provide empirical findings on the following four additional tests: (1) the effect of EPU on decomposed ICS/CCI components according to the survey questions, (2) the effect of EPU on the percentage of "unsure" answers to the ICS/CCI survey questions, (3) the effect of decomposed/categorised EPU components on ICS, and (4) the effect of EPU and its components on producer confidence. The first test allows us to study whether and how EPU influences consumers' perception about the current situation and their expectations about the future differently. The second test verifies whether uncertainty leads to more "unsure" answers, or as we have suggested, leads to more "negative" answers instead. The third test identifies the components and categories of EPU that are more important in determining ICS. Due to the availability of decomposed EPU data, this test is only done for the US data. And the last test replaces ICS/CCI with the confidence on the supplier side. By comparing the similarities and differences in the results for confidence on the supplier side (which we call "producer confidence") and the one on the demand side (i.e., consumer confidence), we can better understand the nature of the relationship between economic policy uncertainty and confidence, and the uniqueness of consumer confidence. In the following four subsections, we discuss the ideas, motivations, methods and results of these four tests respectively.

2.5.1 Influence of Economic Policy Uncertainty on Consumer Confidence Components

As we introduced before, ICS and CCI are both calculated from the answers to several survey questions within a larger survey. In particular, ICS is calculated from the answers to five survey questions, two on current situations and three on future expectations. On the other side, CCI is calculated from the answers to four survey questions, all of which are forward looking. Obviously, there are clear similarity and distinctions between the two consumer confidence measures. This motivates us to study whether and how EPU influences the current component and the expected component of consumer confidence indexes differently.

We think higher economic policy uncertainty may imply bad economy. This effect is linked with lower current personal finance, lower current economic condition, higher unemployment rate, less current buying intention, etc. This effect should be quite strong and stable. However, the relationship may not be causal, as the logic is simply that consumers' current situation and economic policy uncertain are both related to current economy. It also implies that the additional explanatory power of EPU on the current component of ICS could be limited, when other economic variables have also been taken into consideration.

On the other hand, higher economic policy uncertainty may lead to consumer uncertainty about the future. This effect is linked with consumer's pessimism about the future, lower expectations, etc. Therefore, higher economic policy uncertainty is likely to cause lower consumers' future expectations. In other words, unlike the impact on the current component, the impact of EPU on the expected component through a unique channel. Therefore, it should have some additional explanatory power on the expected component of ICS, even when other economic variables are controlled for. Furthermore, when the issue is resolved (for example, when new policies are announced), economic policy uncertainty no longer exists, and the prediction about the future will be adjusted accordingly. Since people are aware of this when they make judgments, economic policy uncertain should not affect consumers' long run expectations as much as it does for the short term ones.

From the discussion, we expect the following findings: economic policy uncertainty has a negative relationship with both the current and the expected components of consumer confidence through different channels. It is likely to *cause* the change in the expected component of consumer confidence. In addition, it should affect the near future expectations more than the long term ones.

Methodology

In the Data Section, we have discussed how ICS for US and CCI for Europe are calculated, and explained for Europe how an index that is equivalent to the ICS for US can be constructed. We can decompose ICS for US (or $\text{ICS}_{\text{equiv}}$ for Europe, which we will omit the subscript in the rest of the section for simplicity) to two components: the current component (ICC), and the expected component (ICE, or $\text{ICE}_{\text{equiv}}$). We can further decompose the expected component of US to question level, which include short-term expectation (y_3) and long-term expectation (y_4). Our objective is to find out whether and how EPU determines the current and expected components of consumer confidence differently. We also would like to check whether EPU determines the short-run expectation and the long-run expectation differently for the US. To achieve these objectives, we use the same approach as in the previous section. in particular, we take the following steps in our data analysis:

1: Correlation. Calculate the correlations of ICS components and EPU, and in particular, corr(ICC, EPU), corr(ICE, EPU). For the US, also calculate corr(y_3, EPU), and corr(y_4, EPU).

2: Regression model. Replace $y =$ICS in Equations 2.3.1, 2.3.2 and 2.3.3 with ICS components. We are still interested in the sign, scale, and significance of the coefficients of the lagged values of EPU, or $\sum_{i=1}^{T^*} \beta_i$, and the change in adj-R^2 from Model 2.3.2 to Model 2.3.1.

3: VAR model. We focus on the (pairwise) Granger Causality results between

EPU and ICS components.

We feel these steps are sufficient for us to compare the results between ICS components. The regression forecast model, the impulse response analysis and variance decomposition are omitted.

Results

The Correlation results are summarised in Table 2.11. For the US, the short term expectation is more highly correlated with EPU than the long term expectation. interesting, in the US, the current component has higher correlation with EPU than the expected component, but the opposite holds for Europe. We will discuss the possible explanations after we present the regression results.

Table 2.11
Correlations of EPU and ICS components

	Correlation with EPU	US	Europe
aggregated index	ICS	-0.626	-0.380
decomposition	ICC (current component)	-0.655	-0.322
	ICE (expected component)	-0.571	-0.405
further decomposition on expected component	y_3 (12-month expectation)	-0.565	
	y_4 (5-year expectation)	-0.494	

The regression results are shown in Table 2.12. From the regression results, we can see that for the US, EPU does not have additional explanatory power on the long-run expectation (notice that $p = 0.281$ when the main variable is y_4). Comparing the ICC (current component) and ICE (expected component) results, we can see that for both US and Europe, EPU has higher relative additional explanatory power (in percentage) on ICE than on ICC. This is consistent with our assumption. EPU influences the expected component by providing new information on the variance of expectations. On the other hand, EPU influences the current component by providing information about current economic condition, which is also included in the control variables. Therefore, EPU should be more valuable in providing unique information for the expected component. We would also like to point out that for the complete model for the US, the coefficient values $\sum \beta_i$ are the same for ICS, ICC and ICE. This might imply that the model is quite robust.

Table 2.12
Influence of EPU on ICS components from Regression Results

	With EPU only (3)			With Z only (2)	With EPU and Z (1)			Incremental [(1)-(2)]
	Adj-R^2	$\sum\beta_i$	p	Adj-R^2	Adj-R^2	$\sum\beta_i$	p	Adj-R^2
US								
ICS	0.406	-0.25	0.000	0.582	0.597	-0.068	0.000	0.015 (2.5%)
ICC	0.435	-0.255	0.000	0.663	0.677	-0.068	0.000	0.014 (2.0 %)
ICE	0.318	-0.217	0.000	0.474	0.487	-0.068	0.001	0.013 (2.7 %)
y_3	0.310	-0.483	0.000	0.460	0.485	-0.205	0.000	0.025 (5.1 %)
y_4	0.232	-0.249	0.000	0.403	0.403	-0.033	0.281	0.000 (0.1 %)
EU								
CCI	0.129	-0.054	0.000	0.173	0.336	-0.074	0.000	0.163 (48.0%)
ICS	0.155	-0.050	0.000	0.166	0.303	-0.058	0.000	0.137 (45.3 %)
ICC	0.110	-0.045	0.000	0.171	0.238	-0.043	0.000	0.067 (28.0 %)
ICE	0.178	-0.056	0.000	0.150	0.353	-0.073	0.000	0.202 (57.4 %)

Note: Refer to Table 2.7 for model specifications. ICS is replaced by ICS components, noted in the first column of the table. Refer to Table 2.11 for variable notation.

The results also explain why corr(ICC, EPU) > corr(ICE, EPU) for US, but not for Europe. Why is EPU more capable of explaining current component in the US, but more capable of explaining expected component in Europe? The regression results tell us that economic variables can explain the current component for US consumer confidence much better than for European consumer confidence. Since the economic variables also influence EPU, the latter can also explain the current component very well. It does not conflict with our expectations.

The Granger causality results are listed in Table 2.13. From the US results, we observe that the current component Granger causes EPU, but the expected component no longer causes EPU. In particular, the long term expectation do not cause EPU. On the other hand, EPU Granger causes all the components. From the European results, we observe that EPU Granger causes the expected components (CCI and ICE) at significance level 0.1, but does not Granger cause the current component (ICC). On the other hand, none of the components Granger causes EPU. Although the results for US and Europe are different, the results are both consistent with our analysis. EPU is more likely to cause expected component than to cause current component. And EPU is more likely to be caused by current component than by expected component. We have discussed that the current component is more "objective" and the expected component is more "subjective". Apparently, the objective part is better explained by economic and financial variables, while the subjective part can not. Therefore, EPU can play a special and unique role in explaining ICS and CCI, due to its use in explaining the subjective part.

In summary, the results are consistent with our main results, and provide new supports to our discussions. The results here show again that for the US, EPU affects ICS through two channels we discussed at the end of the previous section. And they confirm the higher additional explanatory power of EPU on the expected component of ICS, which provides supports on the existence of the second channel. On the other hand, for Europe, it confirms that EPU mainly affects CCI through the second channel.

Table 2.13
Pairwise Granger Causality Results for EPU and ICS Components

Null Hypothesis:	F-Statistic	Prob.
For US (number of lags = 3):		
ICS does not Granger Cause EPU	2.55	0.0553
EPU does not Granger Cause ICS	7.71	0.0001
ICC does not Granger Cause EPU	3.86	0.0097
EPU does not Granger Cause ICC	10.11	0.0000
ICE does not Granger Cause EPU	1.86	0.1367
EPU does not Granger Cause ICE	5.11	0.0018
y_3 does not Granger Cause EPU	2.86	0.0368
EPU does not Granger Cause y_3	5.24	0.0015
y_4 does not Granger Cause EPU	0.39	0.7575
EPU does not Granger Cause y_4	3.31	0.0201
For Europe (number of lags = 3):		
CCI does not Granger Cause EPU	1.11	0.3446
EPU does not Granger Cause CCI	5.87	0.0007
$\text{ICS}_{\text{equiv}}$ does not Granger Cause EPU	1.19	0.3129
EPU does not Granger Cause $\text{ICS}_{\text{equiv}}$	2.91	0.0351
ICC does not Granger Cause EPU	1.12	0.3412
EPU does not Granger Cause ICC	1.76	0.1547
$\text{ICE}_{\text{equiv}}$ does not Granger Cause EPU	0.94	0.4204
EPU does not Granger Cause $\text{ICE}_{\text{equiv}}$	2.62	0.0513

2.5.2 Influence of Economic Policy Uncertainty on Percentage of Unsure Answers in Consumer Confidence Surveys

As we discussed in the previous section, consumer confidence index is calculated by the answers to several survey questions. For both ICS and CCI, the relative score (or "balance") of a question depends only on the percentages of consumers who selected positive or negative answers. However, if we take a look at the options, there are often two more options (at least) exist: neutral answer, and "do not know" or "uncertain" answer (to simplify the notation and avoid confusion, we shall call it "unsure" answers). Both answers are given weights zero in the index calculation. The "unsure" rates gives us an opportunity to test our hypothesis: higher consumer uncertainty leads to lower consumer confidence.

As discussed before, we believe that higher EPU leads to higher consumer uncertainty. When consumers are uncertain about the future, would they be more likely to choose the "unsure" answer? or would they be more likely to choose the "negative" answer? If the latter holds, it proves that consumer uncertainty implies lower consumer confidence. If the former holds, it implies that consumer uncertainty pushes consumer confidence to neutral position, and therefore not necessarily lower.

To check which one is the case, we will study whether EPU determines "unsure" answer rates, and how. We expect to find that EPU does not have a significant and positive relationship with "unsure" rate.

Data

In this section, we focus on the relationship between EPU and unsure rate. We will only focus on the forward looking questions, because the current condition is already known to the consumers. Here, we list the options of each forward looking questions that are related to ICS/CCI calculations.

US

Q2: (1) Better Off, (2) Same, (3) Worse, (4) DK; NA (U_2).

Q3: (1) Good Times, (2) Uncertain (U_{31}), (3) Bad Times, (4) Don't Know (U_{32}), (5) NA (U_{33}).

Q4: (1) Good Times, (2) Uncertain (U_{41}), (3) Bad Times, (4) NA (U_{42}).

Here, we let U_2, U_{31}, U_{32}, U_{33}, U_{41}, and U_{42} denote the percentages of certain answers to a particular question. The design of the questionnaire is quite confusing. Sometimes, "don't know" and "not available" are grouped together (Q2), and sometimes, there are even three answers related to unsureness (Q3). We let

$$t = U_2 + U_{32} + U_{32} + U_{33} + U_{41} + U_{42}$$

to denote the total percentage of unsure answers to all the three forward looking questions related to the calculation of ICS.

Europe

Q1: (1) get a lot better, (2) get a little better, (3) stay the same, (4) get a little worse, (5) get a lot worse, (6) don't know (U_1).

Q2: (1) get a lot better, (2) get a little better, (3) stay the same, (4) get a little worse, (5) get a lot worse, (6) don't know (U_2).

Q3: (1) increase sharply, (2) increase slightly, (3) remain the same, (4) fall slightly, (5) fall sharply, (6) don't know (U_3).

Q4: (1) very likely, (2) fairly likely, (3) not likely, (4) not at all likely, (5) don't know (U_4).

Here, U_i denotes the percentage of consumers who chose the answer "don't know" on Question i ($i = 1, 2, 3, 4$). Let

$$t = U_1 + U_2 + U_3 + U_4$$

to denote the total percentage of unsure answers to all the four forward looking questions related to the calculation of CCI.

Methodology

The objective of this section is to find whether unsure answer rate t increases with EPU. Similar to the previous section on decomposed ICS, we take the following three steps to achieve this goal: first, we take the correlation between U and EPU. Then, we consider the following regression model:

$$U_t = \alpha + \beta \mathrm{EPU}_{t-1} + \epsilon. \tag{2.5.6}$$

We are interested in the sign and significance of β, and adj-R^2 of the model. We expect the sign is either nonpositive, or not significant.

Finally, we check the pairwise Granger causality between these two variables, U and EPU. It is possible that EPU Granger causes U. If it is the case, our explanation is that higher EPU leads to lower unsure rate and higher negative rate.

Results

The Correlation results are summarised in Table 2.14. For the US, the correlation is positive but nonsignificant. On the other hand, for Europe, the correlation is quite negative and significant. Both cases are consistent with our expectations.

Table 2.14
Correlations of EPU and Unsure Rate

US	$p-$value	Europe	$p-$value
0.0735	0.15	-0.565	0.0000

The regression results are shown below. For the US, the estimation equation is as follows:

$$U_t = 29.4 + 0.0169 \times \mathrm{EPU}.$$

The coefficient of EPU is NOT significant ($p-$value $= 0.15$). And adj-$R^2 = 0.003$.

For Europe, the estimation equation is as follows:

$$U_t = 27.4 - 0.0547 \times \mathrm{EPU}.$$

The coefficient of EPU is significant ($p-$value $= 0.0000$). And adj-$R^2 = 0.328$.

The results are quite similar to the correlation result: the relationship is either positive but insignificant, or negative and significant. Note that the constant term α is around 30. Since U is the summation of unsure answers to all forward looking questions, the constant term means that when there is no economic policy uncertainty, the average percentage of people who choose "don't know", "NA" or "uncertain" answers is about $29.4\%/3 = 9.8\%$ for the US. And the average percentage of people who choose "don't know" answers is about $27.4\%/4 = 6.85\%$ for Europe.

The Granger causality results are listed in Table 2.15. From the US results, we observe that EPU and unsure rate do not Granger cause each other. On the contrary, EPU and unsure rateGranger cause each other for Europe.

Table 2.15
Pairwise Granger Causality for EPU and Unsure Rate

Null Hypothesis:	F-Statistic	Prob.
For US (number of lags = 1):		
U does not Granger Cause EPU	1.79	0.1813
EPU does not Granger Cause U	0.41	0.5215
For Europe (number of lags = 1):		
U does not Granger Cause EPU	15.06	0.0001
EPU does not Granger Cause U	4.52	0.0342

From the correlation, regression and Granger causality results, we notice that the results for the US is clearly different from that for Europe. For the US, the relationship between EPU and unsure rate is insignificant, which implies that the unsure rate does not change with EPU. On the other hand, the relationship between EPU and unsure rate is negative and significant, and the explanatory power of EPU is as high as 32.8%. We think, one possible reason for the discrepancy lies in the designs of questionnaires. We can easily identify these differences:

- There is no "NA" choice in the EU survey. This might imply that people must make a choice. On the other hand, "NA" choice is available in the US survey. Note that if "NA" mean people accidentally skip the question or an answer fails to be recorded, its rate should be unrelated to EPU.
- There are more choices in the EU survey, including highly positive, slightly

positive, equal, slightly negative, and highly negative. Maybe by distinguishing the levels, people are less likely to choose "don't know" when EPU is high (due to the availability of the "slightly negative" choice).

- The questions in the US survey are as comparable to each other as the EU one. For example, unlike the EU survey, the choices for the three questions are quite different in the US survey. Moreover, Question Q4 is even an open ended question. And the choice is not even made by consumers directly, but by the interviewer who looks for good versus bad. This may make the US "unsure rate" we constructed less reliable.

Nonetheless, for both countries, there are no significantly positive relationship between EPU and unsure rate. At first glance, it may seem to be counter intuitive. But in fact, it is quite promising. When EPU increases, we expect confidence to decrease, or in other words, we expect more negative answers. We do not expect more unsure answers, as more unsure answers simply make the confidence index at a more neutral position (either decreasing from a positive value, or increasing from a negative one). In conclusion, the analyses on the relationship between "unsure rate" and EPU confirm that uncertainty leads to lower confidence. And the European survey seems better designed to preserve the information due to uncertainty.

2.5.3 Influence of Economic Policy Uncertainty Components on Consumer Confidence

We have been using EPU index as a proxy for economic policy uncertainty. For Europe (and many other countries or areas), the EPU index is constructed based on newspaper articles regarding policy uncertainty. But for the US, the EPU index is a weighted average of four components: news-based index (x_1), expert disagreement (x_2), CPI disagreement (x_3), and tax expiration (x_4). In this section, we study how these four components influence ICS differently. Specifically, we are interested in finding whether the news-based index is a good proxy for economic policy uncertainty, which implies whether the EPU for Europe is trustworthy.

How EPU is decomposed and calculated is already discussed in the Data Section. The methodology is the same as in Section 2.5.1, which includes correlation results, regression model analysis, and Granger causality test from VAR model. Here, we only discuss the main results. All the results are for the US.

The Correlation results are summarised in Table 2.16. The aggregated EPU has the largest correlation (negative) with ICS, which shows that it makes sense to integrate the four components. ICS's correlations with x_2 and x_3 are much smaller, which implies that components 1 and 4 seem to contribute to the large negative correlation between EPU and ICS.

Table 2.16
Correlations of EPU Components and ICS

Correlation with ICS	EPU	x_1	x_2	x_3	x_4
	-0.626	-0.515	-0.213	-0.289	-0.527

Note: EPU = the Economic Policy Uncertainty Index. x_1 to x_4 are components of EPU, which are news-based index, expert disagreement, CPI disagreement, and tax expiration, respectively.

The regression results are shown in Table 2.17. From the regression results, we can see that although x_4 alone explains ICS well, it does not have any additional explanatory power when the control variables are included. This means that the information from tax expiration is already contained in other variables. On the other hand, x_2 and x_3 alone only explains a small portion of the variance in ICS, but they do have a little extra explanatory power when control variables are included. The component that is the most useful is still x_1, the news-based component. It alone explains 28.9% of the variance in ICS, and with control variables, it still explains 1.6% of the variance in ICS.

The Granger causality results are listed in Table 2.18. Only the news component (x_1) Granger causes ICS. Components x_2 and x_3 and ICS do not Granger cause each other at all. And ICS Granger causes x_4, but not the other way around.

In summary, the correlation, regression and Granger causality results show that the news component is the most useful component in explaining ICS. Only this component Granger causes ICS, has large correlation with ICS, and has noticeable

Table 2.17
Influence of EPU on ICS components from Regression Results

	With EPU only (3)			With Z only (2)	With EPU and Z (1)			Incremental [(1)-(2)]
	Adj-R^2	$\sum\beta_i$	p	Adj-R^2	Adj-R^2	$\sum\beta_i$	p	Adj-R^2
EPU	0.406	-0.253	0.000	0.582	0.597	-0.068	0.000	0.015 (2.6 %)
x_1	0.289	-0.188	0.000	0.582	0.598	-0.048	0.000	0.016 (2.7 %)
x_2	0.034	-0.052	0.001	0.582	0.588	0.030	0.012	0.006 (1.0%)
x_3	0.108	-0.149	0.000	0.582	0.592	-0.054	0.002	0.010 (1.7 %)
x_4	0.273	-0.015	0.000	0.582	0.581	-0.000	0.655	-0.001 (0.0%)

Note: Refer to Tables 2.7 and 2.16 for model specifications and variable notation. EPU is replaced by EPU components, noted in the first column of the table.

Table 2.18
Pairwise Granger Causality Results for EPU Components and ICS

Null Hypothesis:	F-Statistic	Prob.
EPU does not Granger Cause ICS	7.71	0.0001
ICS does not Granger Cause EPU	2.55	0.0553
x_1 does not Granger Cause ICS	7.13	0.0001
ICS does not Granger Cause x_1	3.53	0.0152
x_2 does not Granger Cause ICS	0.20	0.8974
ICS does not Granger Cause x_2	1.69	0.1690
x_3 does not Granger Cause ICS	1.34	0.2608
ICS does not Granger Cause x_3	1.13	0.3386
x_4 does not Granger Cause ICS	1.69	0.1678
ICS does not Granger Cause x_4	3.92	0.0089

Note: number of lags = 3.

additional explanatory power on ICS. The results imply that using the news-based economic policy uncertainty index instead of the aggregated one to analyse the relationship between economic policy uncertainty and consumer confidence should not result in very different findings. Therefore, the differences in how EPU is calculated for US and Europe should not be the reason for the different findings.

2.5.4 Influence of Categorised Economic Policy Uncertainty on Consumer/Producer Confidence

In Section , we pointed out that it is also worth explaining why economic variables can influence Consumer confidence, and in what sense EPU changes consumer uncertainty. The two questions seem to be unrelated at the first glance. However, they are actually asking the same question: what economic concept does consumer confidence measure? One theory is that consumer confidence is related to precautionary saving. However, Chatterjee and Dinda (2015) has used simple arguments to prove this is not the case. Instead, they propose that consumer confidence is related to the expectation on the real income (or more precise, "buying condition"). We would like to examine the validity of this theory.

As we discussed in the Data Section, categorised EPUs are available for the US. Therefore, through data analysis, we can find out which categories of EPU are more important in determining ICS. If the categories that are related to consumers' expected income or expense are the more important ones, the theory is supported. To further verify the results, we also compare the results on the relationship between categorised EPU and ICS, with the results on the relationship between categorised EPU and producer confidence. We are interested in finding whether different categories of EPUs would play different roles on confidence on the demand side and confidence on the suppler side, and whether it can be explained by our theory.

Data and Methodology

We focus on the US data, because of the availability of the categorised EPUs. EPU values in 12 categories have been provided. The list of categories can be found in Table 2.3. For the consumer side, we study the relationship between each categorised EPU and ICS, to identify the most important categories in determining ICS. And for the producer side, we use the Business confidence index (BCI) from OECD. According to the official site (`data.oecd.org`), "BCI is based on enterprises' assessment of production, orders and stocks, as well as its current position and expectations for the immediate future. Opinions compared to a 'normal' state are collected and the difference between positive and negative answers provides a qualitative index on economic conditions." It is a component of the bank's business survey, which covers hundreds of companies to assess the business conditions in the country. It is published by the National Bank of their respective nations monthly, and can be regarded as a leading indicator of future developments in the country. Again, we study the relationship between categorised EPUs and BCI, to identify the most important categories, and compare them with the results related to consumer confidence. We expect that the categories related to consumer income expectations or expense expectations should be more important in determining ICS, and the ones related to business expenditures or profit should be more important in determining BCI. In Table 2.19, we discuss the expected findings. We think some categories, such as economic policy uncertainty on *financial regulations*, affect both consumers and producers. On the other hand, certain categories should only have a big impact on the consumer side (such as *health care*), while certain categories should only have a big impact on the producer side (such as *trade*). Similar to the previous sections, we analyse the results based on three aspects: correlations, regression model, and Granger causality test of VAR model.

Table 2.19
Categorised EPUs and their Possible Relationships with ICS and BCI

Categories	**Category Keywords**	**relationship with ICS**	**relationship with BCI**
Economic Policy Uncertainty (c_1)	economic, policy, uncertainty		
Monetary policy (c_2)	c_1+ the fed, central bank, etc	affect loans, etc	affect loans, etc
Taxes (c_3)	c_1+ tax, taxation, etc	affect income	affect profit
Government spending (c_4)	c_1+ government spending, etc		
Health care (c_5)	c_1+ health insurance, etc	affect expense	
National security (c_6)	c_1+ terrorism, war, etc		affect stability
Entitlement programs (c_7)	c_1+ welfare reform, etc	affect income	
Regulation (c_8)	c_1+ regulation, etc		
Trade policy (c_9)	c_1+ import duty, trade treaty, etc		if international
Sovereign debt, currency crises (c_{10})	c_1+ currency crisis, etc		
Financial Regulation (c_{11})	c_1+ banking supervision, etc	affect income	affect profit
Fiscal Policy (c_{12})	c_1+ fiscal stimulus, etc		

Results

Due to the space limit and the dimension of the data, here we omit the data analysis results, but only discuss our main findings:

- The following categories have relatively large correlations with ICS: c_8 (Regulation), c_5 (Health care), $c_1 1$ (Financial Regulation), c_{12} (Fiscal Policy), andc_3 (Taxes).
- The following categories have relatively large additional explanatory power with ICS in the regression models: $c_1 1$ (Financial Regulation), c_8 (Regulation), c_2 (Monetary policy), c_6 (National security), c_{12} (Fiscal Policy), andc_3 (Taxes).
- The following category Granger causes ICS but not the other way around: c_2 (Monetary policy). Many other categories Granger cause ICS and are also Granger caused by ICS.
- The effects of c_9 (Trade policy) and c_{10} (Sovereign debt, currency crises) can be omitted.

Combining the results, we think the EPU in *Regulation* (especial *Financial Regulation*), *Health Care*, *Fiscal Policy* and *Taxes* are the most important categories in determining ICS. The result is consistent with our expectations. These categories have a close relationship with consumers' income expectations. And the categories that are less important are not closely linked with consumers' expectations on their income.

Similarly, we obtain and summarise the results for BCI. We find that *Monetary policy*, *National security*, *Financial Regulation*, and *Taxes* are the most important categories in determining BCI. Indeed, these categories are closely linked with the expected profit from businesses. Compared with the results for ICS, the results are consistent with our expectation. Health Care is no longer important in determining BCI. And National Security is more closely linked with business than with consumers. The only exception is that trade is not important for BCI. This is probably because most businesses surveyed here are local ones.

In summary, the results support our theory: consumer/producer confidence measures expected income/profit. Therefore, the categories related to consumer income expectations impact ICS the most, and the categories related to business expectations impact BCI the most.

2.6 Conclusions

In this chapter, we provided empirical evidence on the role economic policy uncertainty plays on consumer confidence through thorough data analyses. We not only studied the impact of economic policy uncertainty on consumer confidence without or with the presence of major economic variables, but also their dynamics through VAR models. We showed that higher economic policy uncertainty leads to lower consumer confidence, even when the other economic variables are controlled for. We also found that the EPU for US can explain consumer confidence better than Europe, but the additional explanatory power of EPU on ICS is actually smaller for the US than for Europe, adding the control variables. We also did four additional tests to further examine the relationship between economic policy uncertainty and consumer confidence. The additional tests were also useful in showing that (1) uncertainty implies lower confidence (through the analysis on "unsure" answers) and (2) confidence measures income expectation (through the analyses on categorised EPUs).

From all the results, we suggested that economic policy uncertainty affects consumer confidence through two channels. The first channel is that economic policy uncertainty implies current business conditions, and current business conditions affect consumers' income expectations, and therefore affect consumer confidence. On the other hand, the second channel is that economic policy uncertainty causes consumers' uncertainty about their income expectations, and hence affect consumer confidence.

We found that for the US, economic policy uncertainty mainly affects consumer confidence through the first channel. Therefore, its additional explanatory power is small. However, we also found evidence on the existence of the second channel.

For example, economic policy uncertainty Granger causes other variables, and it explains the expected component of consumer confidence better. On the contrary, we found that for Europe, economic policy uncertainty mainly affects consumer confidence through the second channel. It has very large additional explanatory power on consumer confidence, compared with other economic variables.

However, unlike the US, economic policy uncertainty together with economic variables only explain a smaller portion of the variance in European consumer confidence. From the results, and the shapes of the consumer confidence times series for the US and Europe, we suspect that the consumer confidence in Europe may also be influenced by US confidence or variables. In the next chapter, we will study the transactions/spillover effects of consumer confidence across different regions.

Chapter 3

Transmission of Consumer Confidence: International Evidence

3.1 Introduction

In the previous chapter, we studied the determinants of consumer confidence. We focused on the role of economic policy uncertainty, but also included a wide range of economic and financial variables in the model. The results clearly show that although the majority part of consumer confidence can be explained by economic policy uncertainty as well as other more "objective" economic and financial variables, there is always a part that remains unexplained. What is more, the unexplained part is much larger at business turning points. This implies that consumer confidence contains essential and unique information, which is not captured by other variables.

While the model we built was quite solid and robust, and in line with previous research on this area, there is one possible determinant of consumer confidence that was left out of the equation intentionally: the consumer confidence in other countries. From the figures and discussions in the previous chapter, we can clearly observe similar trends for consumer confidence in different countries. They all reached their troughs during the Global Financial Crises, and reached their peaks at similar periods as well. This leads us to wonder: how does the consumer confidence in one country affects that in another country? What can the transmission of consumer confidence tell us? In this chapter, we aim at answering these questions. In other words, instead of focusing on the relationship between other variables and consumer confidence, in this chapter, we focus on the consumer confidence in different countries and regions.

We believe the international transmission in consumer confidence exists for several reasons. First, it is due to the global financial interdependence, which has been widely studied and proven (Cooper, 1985; Longin and Solnik, 1995; Corsetti et al., 2005), and also due to the contagion and co-movements in financial markets, which also attracts research interests (Pericoli and Sbracia, 2003; Ahmad et al., 2013). Intuitively, the interdependence and contagion of the financial market may lead to the interdependence and contagion of consumer confidence among different countries.

Secondly, news has an impact on global financial market (e.g., Albuquerque and Vega (2009); Apergis (2015)). In Chapter 1, we discussed the interpretations of consumer sentiment, and suggests that it contains information such as news that is not included in other financial variables. A property of news is that it spreads over country borders quickly. Therefore, it provides a good channel for the transmission of consumer sentiment.

In addition to economic and financial interdependence/contagion and news effect, there are also social psychological reasons for the transmission of consumer confidence. There is rich evidence for "herd behaviour" of investors in behavioural finance literature (Scharfstein and Stein, 1990). This implies that under certain circumstances, investors simply mimic the investment decisions of others. We can easily extend this idea to general consumers. It is reasonable to suspect that when consumers form their attitude on the willingness to buy (which is measured by consumer confidence), they sometimes simply mimic other people's attitudes.

But it is surprising that although consumer confidence has been used to measure consumer's attitude, the research in "consumer confidence" and the research in "attitude" are quite distinct. While the former is studied under the area of finance, the latter is studied in the area of social psychology. But are they really two different concepts? By Hogg and Vaughan (2009), the definition and measurement method of attitude in social psychology study is as follows:

Attitude is viewed "as a construct that, although not directly observable, precedes behaviour and guides our choices and decisions for action". "Traditionally, attitudes have been measured by using questionnaires."

The concept of consumer confidence suits this definition perfectly. It is indeed not directly observable, precedes people's buying behaviour, and guides our choices and decision when we purchase durable goods. Moreover, consumer confidence is measured by using questionnaires, just as the traditional measurement method for attitude.

Therefore, we think it is important to fill in the gap by linking the research in consumer confidence with the existing findings in social psychology. By this approach, we can better understand what influences consumer confidence, and how consumer confidence affects behaviour. On the other hand, we can use econometrics tools to examine the validity of theories in social psychology when they apply to consumer confidence.

Social psychologists have found that "a crucial source of our attitudes is the actions of other people around us". This implies that a consumer's confidence may be affected by surrounding people's opinions. In particular, group members play an extremely important role in forming ones attitude. "Group norms are enormously potent sources of social influence. They provide us with stable and predictable guides for thinking and behaving." This implies that within a group, group norm may affect each one's confidence as a consumer. They have also found that"the mass media, in particular television, have a major influence on people's attitudes and those of their children - especially so when attitudes are not strongly held (Goldberg and Gorn, 1974)." This finding suggests that consumer confidence is affected by mass media. In a sense, media broadens the boundaries of groups, within which attitudes are shared and influenced more. In summary, by research findings in social psychology, the level of consumer confidence in one area is probably affected by that in many other areas. In addition, the level of conformity is affected by people's status. "Those who conform tend to have feelings of inferiority, feelings of relatively low status in the group, and a generally authoritarian personality". In terms of consumer confidence, it seems to suggest that the consumer confidence of smaller countries might be influenced by that in more powerful countries.

In summary, based on the existing literature in the interdependence of financial markets, the contagion in financial markets, news effects on financial markets, and herding behaviour in social psychology, we suspect that the consumer confidence in one country is affected by that in another country. The level of co-movement and spillover is affected by economic, political and geographic factors. In particular, when consumer confidence changes dramatically in one country (especially a leading one), consumer confidence in other countries may follow the same trend. As mentioned in the previous chapter, consumer confidence is a leading variable. By the discussion here, the large spillover of consumer confidence may even lead the change in consumer confidence in the majority of countries. Therefore, it may have some predictory power, too. Large spillover of consumer confidence has predictive power for economy. In particular, large spillover of consumer confidence collapse may lead financial crises and recessions.

In other words, in this chapter, we aim at answering the following interesting research questions:

1. (The direction of the spillover.) How does the change of consumer confidence in one country affect that in another country? What factors affect the directions of the relationships?

2. (The level of total spillover.) When is the relationship higher than normal situations. What implications does it have?

In Section 2, we will discuss the existing literature in three areas: related findings in social psychology, co-movement and spillover in finance studies, and spillover of consumer confidence. In Section 3, we introduce the data set used for the research, and present the basic statistics and preliminary analysis. In Section 4, we introduce the method we use to answer the first research question, and present and discuss the results. In Section 5, we explain the methods we use to answer the section research question, which include two parts - the construction of spillover index that is used to measure the level of total spillover, and the applications of the spillover index, to evaluate the role it plays in economy. Then we present and discuss the results in Section 6. Finally, Section 7 concludes the chapter.

We think our research findings can provide interesting insights on how consumer confidence of different country affect each other, and what information it may contain. The results will help us better understand the role consumer confidence plays, and be of interest to both researchers and practitioners.

3.2 Literature Review

3.2.1 Literature Review on Financial Interdependence

There is a rich literature that studies international financial interdependence empirically. In general, they analyse the co-movements and contagion between different financial markets. To do this, they often focus on the correlation of asset returns (Corsetti et al. (2005), for example).

It is a problem that is worth studying for several reasons, as listed in Albulescu et al. (2015): it plays a crucial role in portfolios risk assessment, provides clues about spillover effects, and is important for supervision authorities.

The research often focus on the relationship between global market and a specific one, such as Asian or China's stock markets (Morales and Andreosso-O?Callaghan, 2012; Shen et al., 2015), European stock market (Stoica et al., 2015; Tiwari et al., 2016), and US credit market (Shahzad et al., 2017).

The results all confirm the existence of financial interdependence. Shahzad et al. (2017) listed some possible channels of contagion: liquidity issue during crises, updates of judgments, and herding.

Moreover, the co-movement of asset price seems to be higher during crises, and lower during tranquil periods (Corsetti et al., 2005). This finding implies that the level of transmission of financial shocks might be used to identify different regimes (crises and tranquil periods). We will extend this idea to the transmission of consumer confidence. We are going to study whether the level of transmission predicts financial crises.

The research methods often involve factor model of returns (Corsetti et al., 2005), wavelet transform (Albulescu et al., 2015), dynamic conditional correlation (Sensoy et al., 2014), and generalized auto regressive conditional heteroscedasticity (Grammatikos and Vermeulen, 2012). A more detailed summary in table format can be found in Shahzad et al. (2017).

In conclusion, global financial interdependence exists, which supports our hypothesis on the interdependence of consumer confidence. Moreover, the level of co-movement indicates different economic regimes, which prompt us to study how the level of transmission of consumer confidence predicts crises. Finally, the research methods can be adapted to our problem.

3.2.2 Literature Review on Attitude in Social Psychology, and Herding

Herding is an important topic studied in the area of behavioural finance. There are rational and irrational reasons behind it, such as the “sharing the blame// effect, attempting to enhance own reputation, etc (Scharfstein and Stein, 1990).

While herding focuses on investors’ attitude and behaviour that is influenced by other investors, the general topic of attitude formation and influence is studied in the area of social psychology (Hogg and Vaughan, 2009).

In this area, there are a few topics that are closely linked with our research: attitudes and persuasion, conformity, people in groups, and communication. For example, Zimbardo and Leippe (1991) studied the psychology of attitude change and social influence, and confirmed the social influence’s role in changing one’s attitude. Cialdini and Trost (1998) also studied the role of social norms and conformity. On the other hand, Bryant and Oliver (2009) focused on the media effects.

In summary, the research findings in herding, and in social psychology in general, form a theoretical foundation for our research.

3.2.3 Literature Review on the Contagion of Consumer Confidence

While the majority of the researchers analyse the ICS or CCI of the US, research results started to become available for other countries. Most of the studies were country or region specific. For example, Olowofeso and Doguwa (2012) did a panel data analysis to check the relationship between consumer confidence and selective economic variables in Nigeria. Utaka (2003) studied the case in Japan, and concluded that "consumer confidence has an effect on only very short-term economic fluctuations". Berry and Davey (2004) focused on the British CCI. They found out that confidence is determined by economic variables, and non-economic events (the residual element). And the "unexplained" residual term is not closely related to spending. There are only a few papers considering multiple regions. Abeele (1983), Pickering et al. (1983), Lemmens et al. (2007) and Jansen and Nahuis (2003) studied consumer confidence in European countries. Abeele concluded that a few countries' results were inline with that of the US. Pickering et al. observed that different countries and surveys had similar factor structures. Lemmens et al. found that the short-run fluctuations in consumer confidence are largely country specific. Jansen and Nahuis found that "stock returns generally Granger-cause consumer confidence at very short horizons (two weeks to one month), but not vice versa". Özerkek and Çelik (2010) studied the relationships between government spending, consumer confidence, and consumption in six emerging market countries, including Brazil, Czech Republic, Hungary, Poland, South Africa and Turkey. They confirmed confidence's important role, and suggested that consumer confidence can influence consumption by influencing government spending. Golinelli and Parigi (2004) assessed sentiment's predictive power in eight countries across the world (France, Germany, Italy, UK, USA, Japan, Canada and Australia). Curtin (2007) provided a worldwide review of consumer sentiment surveys for forty-five countries. Chatterjee and Dinda (2015) discussed consumer confidence during post-crisis period through a panel data analysis across eleven selected developed or developing economies (USA, UK, France, Germany, Greece, China, India, Japan, Brazil, South Africa and Thailand), and stated that consumers in these countries lost their confidence after 2008, which impacted consumption.

The issue of contagion of consumer confidence is largely omitted in literature. The only piece of work we found is Galariotis et al. (2017). They focused on the impact of monetary policy on economic expectations. But in one section, they also studied the sentiment spillover effects from the US to Core Eurozone countries during the US financial crisis, by a standard variance decomposition (VD) approach. They found that such effects existed. Since it was not the main focus of the research, the results are subject to many limitations. Firstly, only the spillover from US to Europe was studied. Secondly, the use of VD method was questionable, as it was order sensitive. Thirdly, they included many control variables, and hence the consumer confidence contagion problem was not addressed directly.

The contagion of consumer confidence is the focus of our chapter. We will provide a much more complete and thorough approach to study this problem, which resolves all the above mentioned problems in Galariotis et al. (2017).

3.3 Data

Our main focus is to study the contagion of consumer confidence worldwide. To do this, we choose a dataset that contains consumer confidence indexes (CCI) of all the G6 countries (USA, France, Germany, Italy, Japan, and United Kingdom). We focus on these countries because they are six major advanced economies, represent more than 64% of the net global wealth ($263 trillion) (Shorrocks et al., 2013), and they represent countries in three major continents: North America, Europe, and Asia.

We focus on the monthly CCI data from January 1985 to May 2017. Therefore, there are 389 data entries for each country. For CCI data that are only quarterly available (i.e., Japan's CCI before 2004), we take the weighted average of the two adjacent quarters to estimate the monthly values. All the CCI series are downloaded from DataStream.

We study the levels of consumer confidence instead of the first differences. Whether or not to use the differences has prompted controversy ever since Chris Sims in 1980 wrote “Macroeconomics and Reality”. According to Brooks (2019), he points out that ?many proponents of the VAR approach recommend that differencing to induce stationarity should not be done (because the model includes lags already)? Our analyses require the data to be stationary, which the levels of consumer confidence indices satisfy this requirement.

We also want to explain why we include no control variables. The first reason is that the dimension would be too high. We are considering the relationships between every pair of countries. Without control variables, it is already a $n \times n$ matrix for any time point or duration (n = number of countries). But the foremost reason is that studying the consumer confidence series alone would tell us how consumer attitudes transmit among different countries directly. As discussed in the Introduction Section, consumer confidence measures consumer attitude. We do not need or want to decompose the attitude, when we study its transmissions.

In the Additional Analyses section, we also compare the results for G6 countries with the results for a more extended dataset, which contains the CCIs of G6 countries, plus Canada, China, Turkey, Begium, Danmark, Ireland, Greece, Spain, Netherlands, Portugal, Austria, Finland, Sweden, Hungry, and Australia. We show that the results are consistent. In other words, the G6 countries are enough to generate meaningful results for our research problem.

3.3.1 Measurements of Consumer Confidence

In the previous chapter, we already explained how consumer confidence is measured. Here, we briefly summarise the key points.

As we discussed earlier, attitude is not directly observable, and is often measured by questionnaires. Consumer confidence, or consumer attitude, is no exception. In 1946, the first consumer confidence index, University of Michigan’s Consumer Sentiment Index (ICS), was constructed based on answers to five survey questions, and used as a proxy for US consumer confidence. It was at first provided annually, then became quarterly available from 1952 to 1977, and monthly available since 1978.

In Europe, in 1972, the European Commission started to design harmonised surveys (which consists essentially of harmonised questionnaires and a common timetable) to be carried out at national level by partner institutes for different sectors of the economies, including the consumers sector. Consumer Confidence Indexes of the European Union (EU) and applicant countries are now calculated from the answers to four of the survey questions. For major European countries, CCI has been published monthly since 1985.

In Japan, the Consumer Confidence Index has been published by Cabinet Office as a part of "Consumer confidence survey", aims to measure Japanese households' sentiment toward consumption activities. The index consists of four subcategories: overall standard of living, income growth, employment and willingness to buy durable goods. It was quarterly available from 1982 to March 2004, and monthly available afterwards.

Similar consumer confidence surveys are now conducted in almost all developed countries and many developing ones. Currently, the number of countries that publish CCI's regularly have reached at least 45 (Curtin, 2007).

We should point out that the survey questions and weighting methods used to construct CCI indexes are not identical for all the countries. Nonetheless, the survey questions are often related to consumers' personal financial conditions and buying intentions, forecasts on employment, and opinions on overall business conditions. They are found to provide comparable results (Curtin, 2007).

3.3.2 Summary Statistics

The graphs of the CCI's for the G6 countries are shown in Figure 3.1. The summary statistics of the seven series are reported in Table 3.1.

Based on the information from the previous chapter, the theoretical range of ICS for US is from 2 (lowest consumer confidence) to 150 (highest consumer confidence), when neutral value 76 (when the favourable and unfavourable replies are equal). From Table 3.1, we can observe that the actual ICS ranges from 55.3 (indicating 28% more unfavourable answers to favourable ones) to 112.0 (indicating 48.6% more favourable answers to unfavourable ones), with average value 87.4 (indicating 15%

more favourable answers than unfavourable ones). This implies that in general, more consumers have a positive opinion. The Skewness is -0.47 (comparing with Skewness of 0 for normal or other symmetric distributions), indicating the left tail is longer and flatter. This implies that in cases when ICS is lower than average, people can be quite pessimistic, and ICS can be really low (note that the lowest value is 32.1 points below average). These extremely low ICS values often correspond to crises or big events. On the other hand, when ICS is higher than average, it tends to be slightly higher than average (note that the largest value is only 24.6 points above average). This means that unlike crises, there are not "golden times" during which consumers are extremely optimal. Its Kurtosis is 2.88, close to that of a normal distribution (which is 3).

The CCI data for other G6 countries have some similar characteristics. Except for France, the CCI always has a negative skewness, indicating the existence of some extremely low values. And the Kurtosis is always around 3, indicating the similarity to a normal distribution.

The CCI data for other countries also show some differences. the theoretical range of CCI's for European countries is from -100 (100% strong unfavourable answers) to 100 (100% strong favourable answers), with neutral value 0 (same percentage of favourable and unfavourable answers). The actual index ranges from -37 to 3.3 with an average of -18.7 for France, from -32.9 to 10.9 with an average of -7.1 for Germany, from -41.5 to 2.5 with an average of -15.3 for Italy, and from -35.2 to 7.6 with an average of -8.6 for the UK. Unlike ICS for US, CCI's for Europe are below the neural value most of the time, and has lower variance. This implies that on average, the European consumers might be more pessimal about the economic and buying conditions than US consumers. On the other hand, the statistics of Canadian consumer confidence index is quite similar to that of US. And the Japanese consumer confidence has a much lower standard deviation (partly because part of the original data were quarterly available).

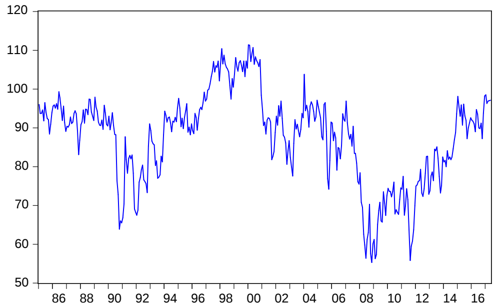
From Figure 3.1, we can observe that US consumer confidence dropped sharply in around 1990 (due to Gulf War) and from 2007 to 2009 (due to the Global Financial Crisis). Among the sharp drops, the most recent Global Financial Crisis seems to have the largest and the most prolonged impact. ICS reached its historical low in November 2008 (at value 55.3) after over a year's almost monotonic decrease. The recovery of ICS is also quite slow, which takes more than five years. Interestingly, ICS dropped again to a nearly historical low value in August 2011 (at value 55.8), when the Great Recession was already officially ended (according to NBER's Business Cycle Dating Committee, the Great Recession started in December 2007, and ended in June 2009). This shows that consumers were as pessimistic about the US economy as they were in the middle of the Great Recession.

In Figure 3.2, we rescaled all the consumer confidence data to [0, 1], and plotted the seven time series on the same graph. Interestingly, it clearly shows some similarity of the series, and CCI's for other countries tend to change in the same direction as ICS for US (sometimes with a small lag). For example, for most countries, the consumer confidence reached historical low in early 2009, due to the Global Financial Crises. They also drop in or around 2012, probably due to the Euro crises. Moreover, they reached their local minimum in 1990-1992, around the time of the Gulf War. The similarity of the time series shows that although European consumers are generally more pessimal than US consumers, the change in their confidence still provides similar information to the change in US consumers' confidence. On the other hand, the series also have some clear differences. For example, Japan's consumer confidence only follows the same trend loosely. Germany's consumer confidence reached its maximum in Nov 2011 - a quite different move from other countries. And instead of 2009, Italy's consumer confidence dropped to its global minimum in June 2012, which is not quite surprising, because Italy was one of the countries that was at the centre of the European debt crisis.

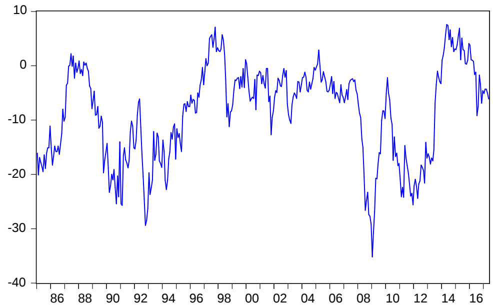
The similarities in the trend imply that the consumer confidence in different countries are indeed connected with each other. The consumer confidence in one country is likely to be influenced by that in another country. On the other hand, the differences in the trend make the directions and magnitudes of the connections unclear. In the next sections, we will use quantitative tools to untangle this problem.

Figure 3.1
Consumer Confidence Indexes for G6 Countries

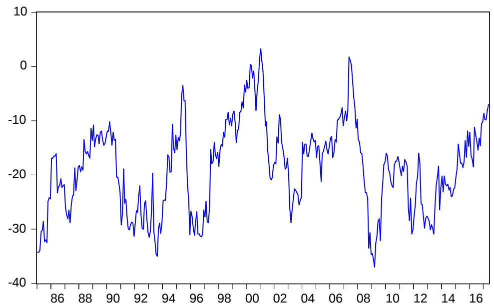
(a) ICS of United States



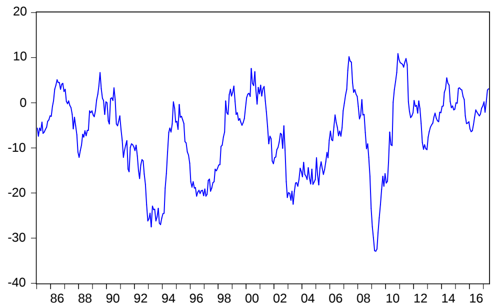
(b) CCI of United Kingdom



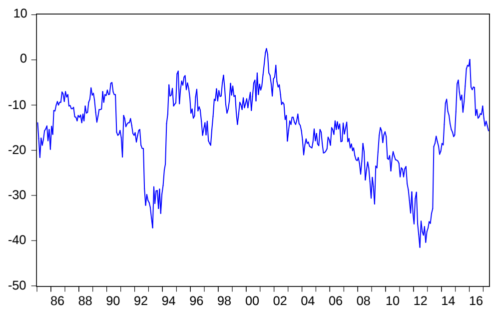
(c) CCI of France



(d) CCI of Germany



(e) CCI of Italy



(f) CCI of Japan

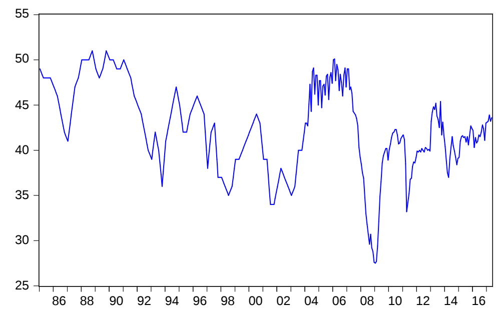


Figure 3.2
Consumer Confidence Indexes of G6 Countries (Rescaled to [0, 1])

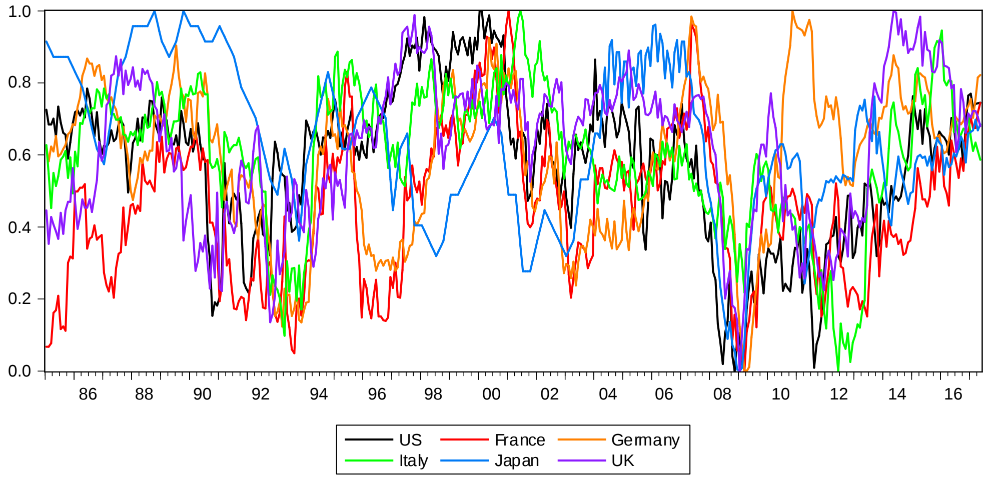


Table 3.1
Summary Statistics of Country Specific Consumer Confidence Indexes

	US	FR	DE	IT	JP	UK
Mean	87.6	-18.7	-7.1	-15.3	42.4	-8.6
Median	90.6	-17.9	-5.4	-14.0	42.0	-6.5
Maximum	111.4	3.3	10.9	2.5	51.0	7.6
Minimum	55.3	-37.0	-32.9	-41.5	27.5	-35.2
Std. Dev.	11.8	8.2	9.0	8.5	4.9	8.7
Skewness	-0.52	0.13	-0.50	-0.82	-0.36	-0.44
Kurtosis	2.94	2.54	2.65	3.43	2.91	2.37
Jarque-Bera	17.27	4.42	18.42	46.33	8.47	19.25
Probability	0.00	0.11	0.00	0.00	0.01	0.00

Note: US = United States; FR = France; DE = Germany; IT = Italy; JP = Japan; UK = United Kingdom.

3.4 Directional Spillovers of Consumer Confidence

This chapter is on the transmission of consumer confidence. In this section, we focus on the "direction" of the transmission. In other words, we aim at providing answers to our first research question: does the change of consumer confidence in one market lead that in another market?

3.4.1 Methodology

In order to find empirical evidence for the research problem, we analyse the G6 country CCI data through Vector Autoregression (VAR) model analysis. In particular, we consider a VAR model which only include the six main variables - the CCI series of six countries, all as endogenous variables. The model has the following format:

$$Y_t = A_0 + \sum_{i=1}^{T^*} A_i Y_{t-i} + u_t,$$

where Y_t denotes the endogenous variable vector, u_t denotes the error vector that satisfies certain criteria, A_i denotes the coefficient vector, and T^* denotes the optimal number of lags.

Once we have estimated a VAR model, we are also able to analyse its properties using structural analysis, or in particular, the Granger causality test. We do both pairwise Granger causality test between the variable pairs, and Granger causality test for the complete model (with six variables). In particular, to test whether EPU pairwise Granger causes ICS/CCI, we consider the following model:

$$y_t = a_0(1) + \sum_{i=1}^{T^*} a_i(1,1) y_{t-i} + \sum_{i=1}^{T^*} a_i(1,2) x_{t-i} + u_t(1). \tag{3.4.1}$$

And to test whether EPU Granger causes ICS/CCI in the complete model, we consider the following model:

$$y_t = a_0(1) + \sum_{i=1}^{T^*} a_i(1,1) y_{t-i} + \sum_{i=1}^{T^*} a_i(1,2) x_{t-i} + \sum_{i=1}^{T^*} B_i(1) Z_{t-i} + u_t(1). \tag{3.4.2}$$

In both cases, we test the joint hypothesis:

$$a_1(1,2) = a_2(1,2) = ... = a_{T^*}(1,2) = 0,$$

with Null hypothesis being x does not Granger cause y.

Under the VAR model, we also perform variance decomposition (VD), which provides information about the relative importance of each random innovation in affecting the variables in the VAR. Specifically, the variance decomposition results tell us in the short run (for example, at the 2nd month) and in the long run (say, in 10 years), shock to CCI in one country accounts for how much variation of the fluctuation in CCI in another country. In stead of the standard VD approach, which is sensitive to data ordering, we follow the approach in Diebold and Yilmaz (2012). They provide a novel approach to variance decomposition, so the results is invariant to variable ordering (which they call "spillover"). Moreover, they propose measures of directional volatility spillovers, which suits our research objective perfectly.

3.4.2 Results and Discussions

We first calculate the correlation matrix for all the six main variables.

Table 3.2 presents the correlations among all the six consumer confidence variables used in our study. The correlations between two countries are all positive and significant. For most countries, CCI's have the largest correlation with the US CCI. And the correlations between the four European countries' CCI's are often quite large. On the other hand, Japan's CCI has a much lower correlation with other countries' CCI's. The results seem to indicate the US's consumer confidence is closely linked with other countries' CCI's, and European countries are closely linked with each other.

The correlation results do not tell us about the direction of the relationship. And they only imply the level of co-movement among the consumer confidence data, not the "leaded effect". Therefore, we move to the VAR model to address these issues.

For the VAR model, the optimal number of lags according to Akaike information criterion is 2. The pairwise Granger Causality results are summarised in Table

Table 3.2
Correlation Matrices

Correlation Probability $\|t\| = 0$	US	GERMANY	FRANCE	ITALY	JAPAN	UK
US	1 ——					
GERMANY	0.13 0.012	1 ——				
FRANCE	0.48 0.0000	0.53 0.0000	1 ——			
ITALY	0.59 0.0000	0.28 0.0000	0.48 0.0000	1 ——		
JAPAN	0.27 0.0000	0.19 0.0002	0.14 0.0064	0.17 0.0007	1 ——	
UK	0.57 0.0000	0.11 0.028	0.42 0.0000	0.53 0.0000	0.085 0.095	1 ——

3.3. When only two variables are considered in pairs, at test critical value 5%, US consumer confidence Granger causes the consumer confidence in all the other five countries. France CCI Granger causes UK and Germany CCI's. And Italy CCI Granger causes Germany CCI. Japan and Germany's CCI's Granger cause each other.

The Granger Causality results for the complete 6 variable VAR model are summarised in Table 3.4. The results are similar to the pairwise one. It shows that at test critical value 5%, US consumer confidence Granger causes UK, France, Italy and Japan's CCI's. In addition, France CCI Granger causes UK and Germany CCI's. And Italy CCI Granger causes Germany CCI. Again, the results show the US's special role in consumer confidence transmission, and also indicate the higher connection among European countries.

Table 3.5 and Figures 3.3, 3.4, 3.5, and 3.6 shows the directional spillover (variance decomposition) results based on Diebold and Yilmaz (2012). The results clearly show that US is the biggest generator of spillover, whose contribution is much higher than any other country. On the other hand, the four European countries (France,

Table 3.3
Pairwise Granger Causality

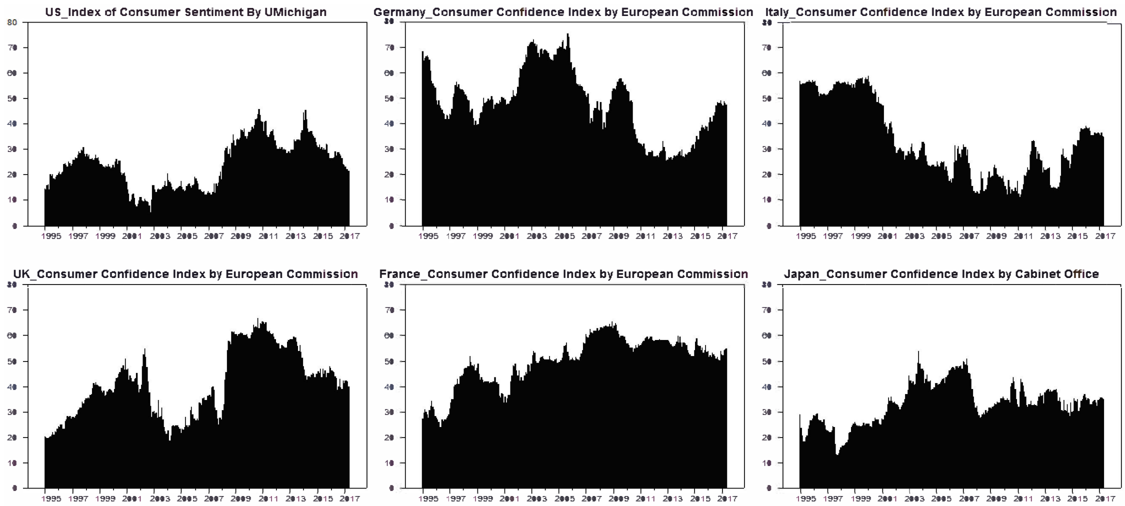
Null Hypothesis:	F-Statistic	Prob.
GERMANY does not Granger Cause US	2.1	0.12
US does not Granger Cause GERMANY	5.2	0.0061
FRANCE does not Granger Cause US	2.2	0.12
US does not Granger Cause FRANCE	8.7	0.0002
ITALY does not Granger Cause US	0.29	0.75
US does not Granger Cause ITALY	6	0.0026
JAPAN does not Granger Cause US	0.043	0.96
US does not Granger Cause JAPAN	5.7	0.0038
UK does not Granger Cause US	0.84	0.43
US does not Granger Cause UK	8.6	0.00023
FRANCE does not Granger Cause GERMANY	8.7	0.0002
GERMANY does not Granger Cause FRANCE	2.5	0.084
ITALY does not Granger Cause GERMANY	6.2	0.0022
GERMANY does not Granger Cause ITALY	2.3	0.1
JAPAN does not Granger Cause GERMANY	3.6	0.028
GERMANY does not Granger Cause JAPAN	3.5	0.03
UK does not Granger Cause GERMANY	1.6	0.21
GERMANY does not Granger Cause UK	1.5	0.23
ITALY does not Granger Cause FRANCE	1.6	0.21
FRANCE does not Granger Cause ITALY	1.7	0.18
JAPAN does not Granger Cause FRANCE	2.1	0.13
FRANCE does not Granger Cause JAPAN	1.1	0.33
UK does not Granger Cause FRANCE	2.9	0.054
FRANCE does not Granger Cause UK	5.6	0.0039
JAPAN does not Granger Cause ITALY	1.2	0.29
ITALY does not Granger Cause JAPAN	0.25	0.78
UK does not Granger Cause ITALY	0.59	0.55
ITALY does not Granger Cause UK	1.4	0.26
UK does not Granger Cause JAPAN	0.38	0.69
JAPAN does not Granger Cause UK	0.099	0.91

Table 3.4
Granger Causality Results for the Complete VAR Model

Excluded	Chi-sq	Prob.
Dependent variable: US		
UK	2.44	0.296
FRANCE	2.48	0.289
GERMANY	1.98	0.372
ITALY	1.35	0.509
JAPAN	0.437	0.804
All	10.4	0.409
Dependent variable: UK		
US	10.5	0.00525
FRANCE	6.81	0.0332
GERMANY	0.632	0.729
ITALY	2.23	0.329
JAPAN	0.261	0.878
All	28.1	0.00173
Dependent variable: FRANCE		
US	9.61	0.0082
UK	0.717	0.699
GERMANY	4.48	0.106
ITALY	0.198	0.906
JAPAN	0.801	0.67
All	23.8	0.00804
Dependent variable: GERMANY		
US	1.69	0.43
UK	0.711	0.701
FRANCE	10	0.00662
ITALY	11.8	0.00271
JAPAN	4.32	0.115
All	37.5	$4.69E-05$
Dependent variable: ITALY		
US	6.45	0.0398
UK	0.248	0.884
FRANCE	0.718	0.698
GERMANY	2.37	0.306
JAPAN	0.657	0.72
All	16.2	0.0928
Dependent variable: JAPAN		
US	10.1	0.00653
UK	0.227	0.892
FRANCE	0.512	0.774
GERMANY	4.05	0.132
ITALY	0.0598	0.971
All	17.9	0.0568

Note: optimal number of lags by Akaike information criterion is used. In particular, $T^* = 2$.

Figure 3.3
Directional CCI Spillovers, FROM All Countries



UK, Germany, and Italy) are the biggest receivers of spillover. Within these four countries, they contribute to and from each other at different time points. These results imply the role each country plays, which is consistent with our findings based on the Granger causality test.

Table 3.5
Summary of Spillovers

	US	UK	Germany	FRANCE	ITALY	JAPAN	From Others
US	87.95	3.78	2.26	1.75	3.42	0.85	12.0
UK	13.00	75.81	0.38	1.60	8.78	0.43	24.2
Germany	6.74	0.89	77.88	9.32	1.28	3.89	22.1
FRANCE	22.27	3.66	3.25	68.78	0.47	1.56	31.2
ITALY	13.58	4.07	0.65	1.57	79.56	0.57	20.4
JAPAN	5.23	0.57	1.25	0.18	0.06	92.70	7.3
Contribution to others	60.8	13.0	7.8	14.4	14.0	7.3	117.3
Contribution including Own	148.8	88.8	85.7	83.2	93.6	100.0	19.6%

Figure 3.4
Directional CCI Spillovers, TO All Countries

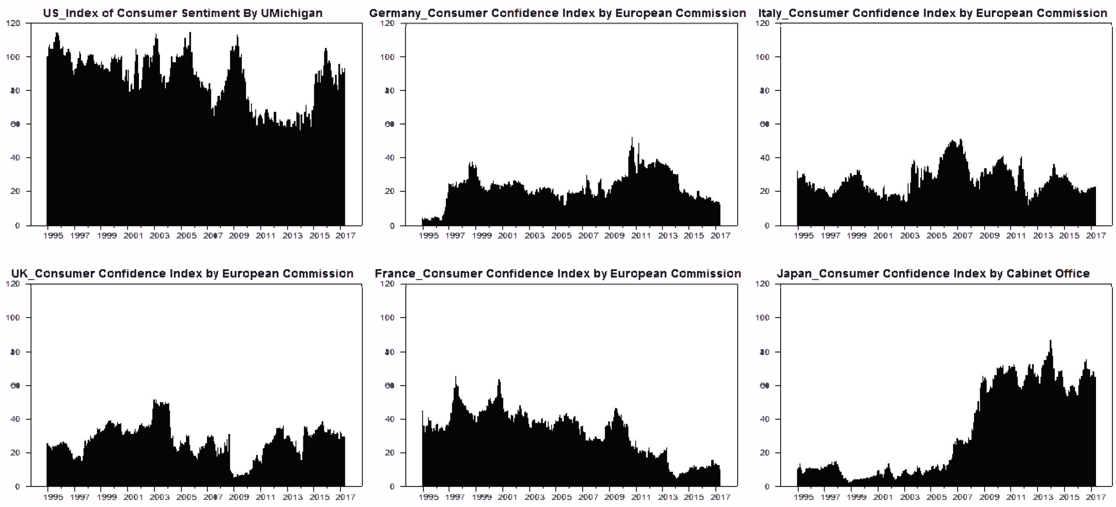


Figure 3.5
Net CCI Spillovers

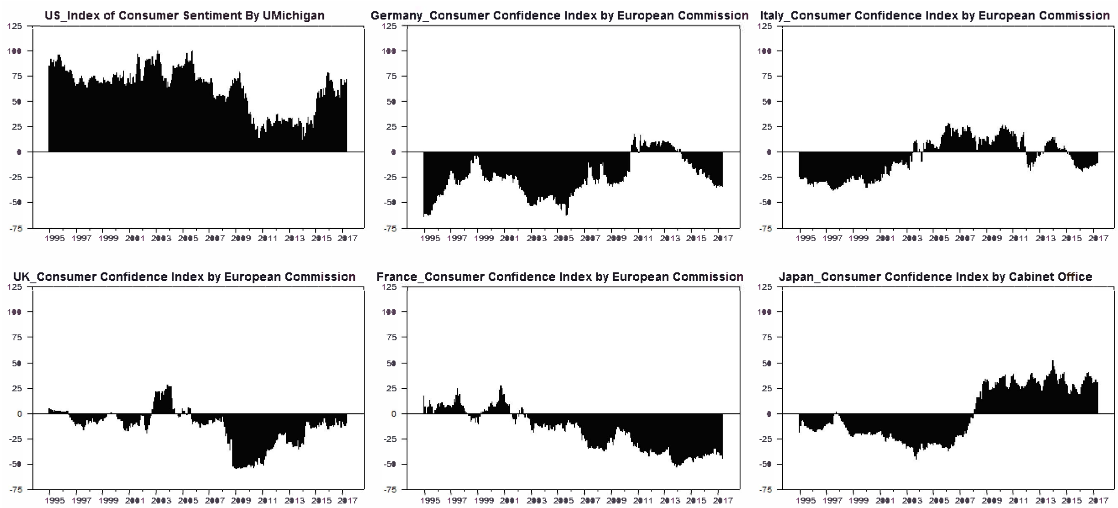
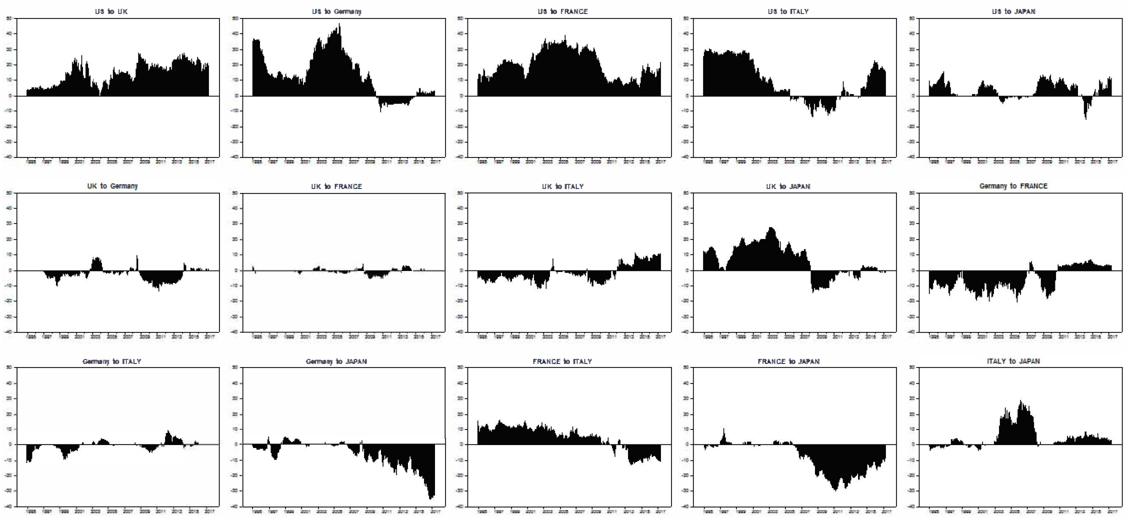


Figure 3.6
Net Pairwise CCI Spillovers



3.5 Total Spillover of Consumer Confidence

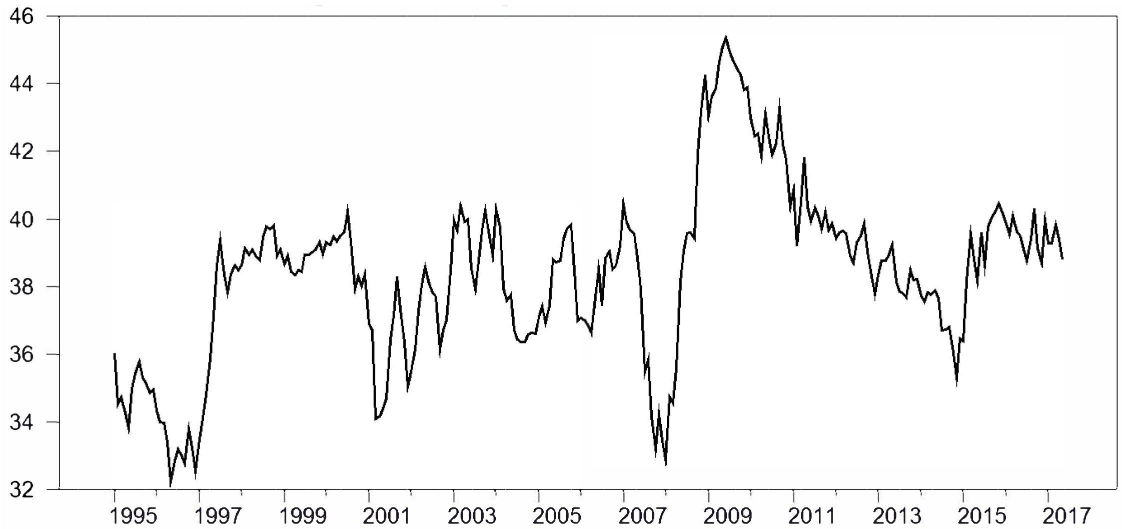
3.5.1 Methodology

In stead of "Directional Spillovers" which focus on the transmission of consumer confidence from a country to another country, in this section, we study the total level of spillovers. Obviously, the total spillover can be obtained by adding the net spillovers of each country together. In this section, we still follow the approach in Diebold and Yilmaz (2012) to obtain total spillover of consumer confidence. In specifically, we choose a moving window of 120 months (i.e., nspan = 120) for a meaningful results. To simplify the notation, we call this series Consumer Confidence Spillover Index (CCSI).

In order to understand the role of total spillover of consumer confidence, we also transform CCSI so that the periods with high, moderate, or below average spillovers can be identified.

In particular, we follow the approach in Chau and Deesomsak (2014) to calculate the scored spillover index Z, which measures how many standard deviations the current CCSI is away from its time-varying mean. The value distinguishes four distinct regimes of spillover severity. Mathematically, Z = how many standard deviations (SD) the current CCSI is away from its time-varying mean. = (CCSI -

Figure 3.7
Total Spillovers, All G6 Countries



time varying mean) / (time varying standard deviation). Here, we choose 50 months as the time window length.

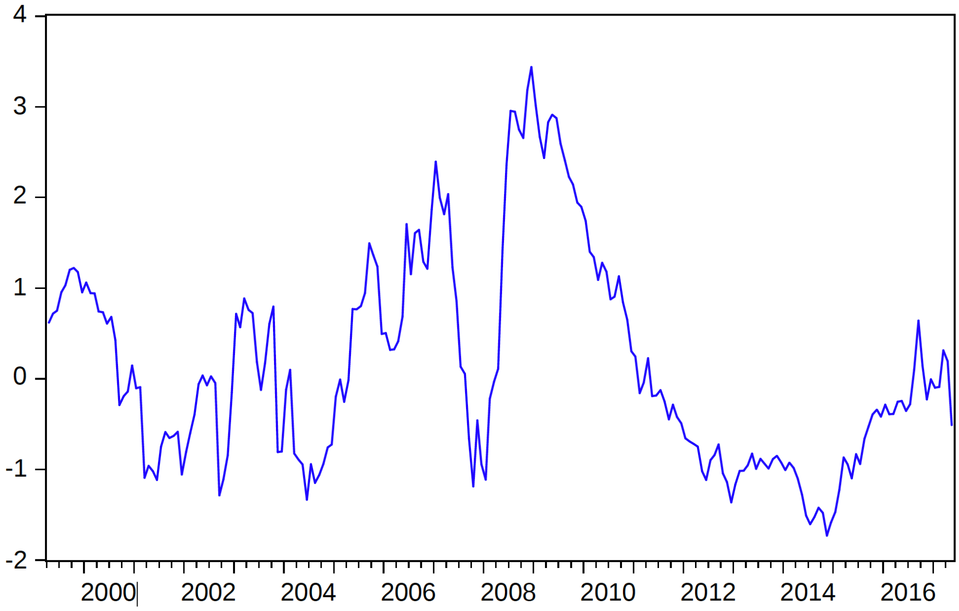
When Z is larger than 2 SD above the mean, it is classified as "severe spillover"; when Z is between 0.75 and 2, we consider the spillover as "moderate"; $Z \in [-0.75, -0.75)$ is classified as normal spillover, and $Z < -0.75$ is classified as below-normal spillover.

3.5.2 Results and Discussions

The CCSI series is shown in Figure 3.7. From the figure, we can see that the total spillover reached its peak in early 2009, during the Global Financial Crises. There was a large escalation from early 2008 all the way from a nearly historical trough to this peak. This makes us wonder: does the high escalation in total spillover level tell us something about economy? does it have any predictory power?

The transformed Z series is shown in Figure 3.8. The results show that during the last 18 years, there are briefly two time periods that are classified as having "severe spillover" (i.e., $Z > 2$): the beginning of 2007 (January 2007 and April 2007), and from June 2008 all the way to October 2009. The severe spillover seems to be an indicator of severe problem, such as crises or recessions. In the next section,

Figure 3.8
Transformed Total Spillovers, All G6 Countries



we will analyse the implications of total spillover levels in more detail.

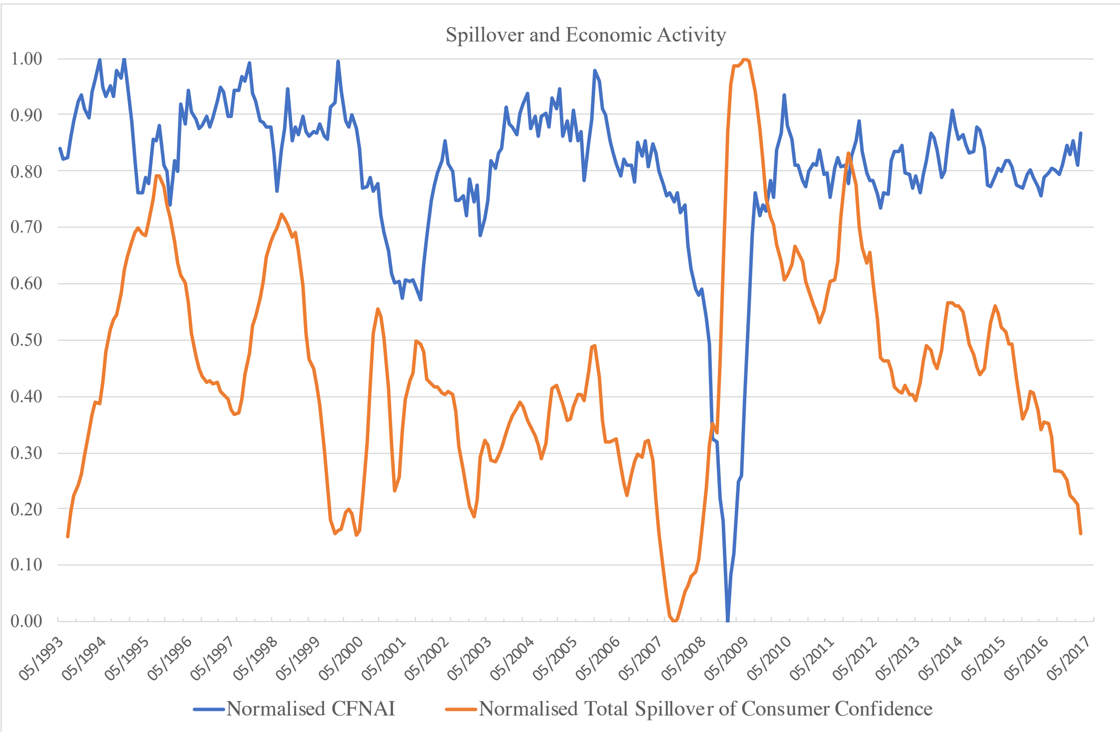
3.6 Use Total Spillover of Consumer Sentiment to Predict Economic Activity

In this section, we study the application of of Consumer Confidence Spillover Index (CCSI). We think it is interesting to determine whether and to what extent the transmission of consumer sentiment affects the economic activity. We use the Chicago Fed?s National Activity Index (CFNAI) as a measure of the overall US economic activity. It was developed by Stock and Watson (1999), using principal components of 85 monthly indicators for employment, production, etc, and has been proven useful in providing information on the current and future courses of US economic activity and inflation.

The graphs for both CFNAI and CCSI are plotted in Figure 3.9. The two indices show a negative relationship, especially at their turning points.

We use a VAR model to further study the relationship between CCSI and CFNAI. The research method is similar to that in Chapter One. Specifically, we followed

Figure 3.9
CCSI and CFNAI



Note: blue line = Chicago Fed's National Activity Index (CFNAI). orange line = Consumer Confidence Spillover Index (CCSI). Both linearly normalised to range [0,1] for easier comparison.

the approach in Chau and Deesomsak (2014). We regard CFNAI as the dependent variable, CCSI as the main independent variable, and also included two control variables: interest rate and CPI. For the data range, we include the monthly data between August 1993 and Apr 2017 (which gives us 280 data points). The VAR results show that CCSI Granger causes CFNAI (with F statistic = 4.01), but not the other way around (with F statistic = 1.93). Moreover, it has significant additional explanatory power (9%). As we expected, we can conclude that the total spillover can be used as a good indicator of economic activity.

3.7 Future Research

3.7.1 Predict Financial Crises

The total spillover of consumer confidence can have other applications.

We can study the relationship between total spillover and financial crises. First, we need to build a logit model in which the dependent variable is a binary indicator for crises. Obviously, we do not have a universal rule to identify crises and their durations. Therefore, we can use the time of recessions by NBER as an indicator. On the other hand, the independent variable is the total spillover level. From the results, we expect spillover to be a predictor for crises. Due to the limitation in scale of the thesis, this part will be done in the future.

3.7.2 Spillover of Filtered Consumer Confidence Data

We can further process the consumer confidence data first, so that to focus on the spillover of specific consumer confidence changes.

There are two approaches to “filtering” consumer confidence. The first approach is the “residuals” approach. Under this approach, we can build a VAR model first, having consumer confidence as the dependent variable, and a group of economic and financial variables as independent variables. This is quite similar to what we did in Chapter One. After we estimate the VAR model, the residuals will be used as the filtered consumer confidence. The underlying reason is that this residual is the part of consumer confidence that is not explained by other variables.

The second approach is the "asymmetry" approach. Under this approach, we can separate the downward changes in consumer confidence and the upward changes, into two distinct series. And we will be able to study and compare the spillovers of the two consumer confidence series.

3.8 Conclusions

In this chapter, we study the transmission of consumer confidence around the globe. In particular, we focus on the G6 countries, and study two problems: the directional spillover of consumer confidence, and the total spillover. The former focuses on the "direction" of the relationship. We are able to identify each country's role - who are the receivers, and who are the contributors, and why. We have found that US has by far the largest influence on the spillover of consumer confidence. This is not surprising, given it being the largest economy in the world. We have found that European countries, due to the close economic and geographic relationships, also influence each other frequently. But each country's role is time dependent, and is worth further study.

The second problem focuses on the "magnitude" of the relationship, and its applications. We find that spillover is the highest at the beginning of a financial crises. Therefore, it has some predictory power on economic activities and economic turning points. This is because a large drop in consumer confidence in one country often leads large drops in consumer confidence in other countries, which in turn is a warning sign to world economy.

In this chapter, our research is motivated by theories and findings in the area of social psychology. Our research findings verify these findings, and hence provide some proof on what consumer confidence measures - consumer attitude.

Chapter 4

The dynamics of sentiment and house price

4.1 Introduction

The focus of the thesis is consumer sentiment. In Chapter 1, we studied the determinants of consumer sentiment, focusing on the role of a new variable, Economic Policy Uncertainty. In Chapter 2, we studied its interactions among different countries. From the results in Chapter 1, we found that the economic variables can explain part of consumer sentiment, and our new variable has extra explanatory power. Nonetheless, there is part of consumer sentiment that is left to be unexplained by other variables. This implies the consumer sentiment may have unique information in itself, and it may have unique explanatory power on other economic variables that may interest us. Hence, in this chapter, we study the effects of consumer sentiment on other variables, or specifically, on house price.

There is wide literature on the effects of consumer sentiment. Some focus on how consumer confidence affects expenditure of durable goods, for instance, Leone and Kamakura (1983); Bram and Ludvigson (1998); Ludvigson (2004); Özerkek and Çelik (2010). Most researchers agree that consumer sentiment do have some unique information that helps predict future expenditure. And on the other hand, some focus on the relationship between sentiment and stock market performance, such as Friend and Adams (1964); Scharfstein and Stein (1990); Jansen and Nahuis (2003);

Baker and Wurgler (2006); Allis and McCallig (2007); Bollen et al. (2011); Baker et al. (2013). The general finding is that investment sentiment affects the investment.

However, There is limited evidence on the effects of consumer sentiment on house price, possibly because of the unique characteristics of house purchase. It can be regarded as both a durables/services consumption, as well as an investment. Therefore, the relationship between consumer sentiment and house price becomes more ambiguous and complicated, and is worth studying.

Researchers have been interested in finding the determinants of house price for a long time. Apparently, the level of demand and supply determines price. Housing market is not an exemption. House price is determined by the demand and supply factors. Higher demand and lower supply lead to higher house price. Following this idea, researchers have confirmed that the housing market is influenced by the state of the economy, interest rates, real income and changes in the size of the population, etc.

However, in addition to these economic factors, people also agree that sentiment plays a role in house price change. But what role it plays depends on how to interpret it. Based on Ludvigson (2004), one economic interpretation is that it captures reduced uncertainty about future, and therefore diminishes precautionary savings motives. In other words, higher sentiment implies higher expenditure today, and lower expenditure in the future. As a result, consumer will save less, and consumption growth will be lower in the future. If it is the case, consumer sentiment might be negatively related to house price. In Chapter 2, we suggest that consumer confidence partially measures uncertainty, which is aligned with this explanation. However, this interpretation is rejected by the economic evidence according to Ludvigson (2004).

The other interpretation proposed by Ludvigson (2004) is that consumer sentiment captures the expectations of future income. It is founded on the rational expectations – permanent income hypothesis (REPIH). If consumer sentiment higher, it implies that consumer expects higher income and wealth in the future. Consumption expenditure might increase today, since consumers should be able to borrow against their future income and wealth, and smooth consumption over time. Or, if consumers follow a "rule of thumb", i.e., consuming current income, or if they are liquidity constrained, they might not be able to consume right away, but will be able to consumer more as their income because higher. This interpretation is supported by the analysis between consumer sentiment and consumption data.

However, Ludvigson (2004) also points out that although consumer sentiment seems to imply future income expectations, it has unique information that is not included in income data. This is related to our findings in Chapter 1. We also suggest that consumer sentiment is not a measure of animal instinct, but a reflection of information (such as news) people receive that is not included in other economic or financial variables. Based on the information, people have a better understanding of world news and big events, world economy, the economic environment around them, and their future income expectations. If we interpret consumer sentiment this way, it should have a positive relationship with both people's willingness to buy, and the willingness to invest. Moreover, its expectation component (the prediction part) might even have a stronger prediction power, due to the liquidation constraint at the current stage. Nonetheless, when consumer sentiment is higher, not only do consumers expect to have more money, they also expect other people to have more purchasing and investment power. Hence, we make the following hypothesis:

Hypothesis 1: *Higher consumer sentiment leads to positive change in house price.*

Consumers include a large group of people. In general, almost everyone of us is a consumer. More specifically, the consumer sentiment represents the sentiment of people who take the Survey of Consumers. These people belong to different demographic subgroups. They are from different regions, at different ages, and with different income. Obviously, consumers within different demographic subgroups do not affect house price in the same manner. For example, people in a very young age group are less likely to be potential home buyers. Hence, their sentiment may not affect house price as much as middle-aged people do. On the other hand, very old people are less likely to buy a new house as well, which also makes their sentiment less important than middle-aged people's one in determining house price. The discussion leads to the following hypothesis:

Hypothesis 2(a): *The sentiment of middle-aged people plays a better role in explaining the change in house price.*

Similarly, consumers with higher income are more likely to be potential home buyers, and they tend to be more knowledgeable on the financial market. Hence, their sentiment is likely to play a more important role in determining house price change. This leads to the next hypothesis:

Hypothesis 2(b): *The sentiment of people with higher income plays a better role in explaining the change in house price.*

Whether and how the sentiment of consumers from different regions works differently is harder to discuss intuitively. However, there are clearly regional differences in house price, income levels, population, etc. Therefore, we also make Hypothesis 2(c) and we are interested in finding empirical evidence and discovering how consumer sentiment works within different regions.

Hypothesis 2(c): *There could be a region difference in the role of consumer sentiment on explaining the change in house price.*

In the previous few paragraphs, we considered the decomposition of consumer sentiment into different demographic subgroups. On the other hand, the house price can also be further decomposed. There are more expensive houses in the top price tier, and more affordable houses in the bottom tier. While the latter are more likely to be a "necessity" for people, the former is more of a "luxury' item". We think consumer sentiment may affect the purchase of the houses in a higher price tier more. Because while people have to purchase necessary items all the time, sentiment gives people more incentive to buy luxury items they otherwise are reluctant in buying. Hence, the following hypothesis is made:

Hypothesis 3: *Consumer sentiment explains the change in the price of houses within higher price tier better.*

We have discussed the role of consumer sentiment on house price change in detail. We need to point out that consumer sentiment captures people's optimism in buying, but not in buying a house in particular. This makes us wonder, can we construct a housing specific consumer sentiment index, which gives more weight on people's opinions on the housing market?

Moreover, while our focus has been consumer sentiment through this thesis, when thinking of the housing market, we think some professional opinions/sentiment can also provide some extra value. Consumers are potential home buyers. On the contrary, home sellers (or builders)' opinions would reflect the demand of the housing market and the supply of the housing market. Therefore, builders' sentiment is also important. Similar to consumer sentiment, builders' sentiment shows the builders' view on the housing market. If their sentiment is high, it implies that they feel they are going to sell more houses and make more money, which means the demand is going up and the house price is likely to go up accordingly.

In addition, realtors, or real estate brokers, are agents who create a bridge between consumers and builders.They are people who represent sellers or buyers of real estate or real property. As professionals, their sentiment should reflect the demand and supply of the housing market quite well. As a result, realtors' sentiment should also be very useful in determining house price.

Finally, the demand of the housing market is affected by the lenders, or mortgage providers. Therefore, their opinions also provide unique information in determining house price.

Fortunately, the data that represent sentiment of builders, lenders and realtors are accessible. By combining the opinions of consumers, builders, lenders and realtors, we think we can construc a new sentiment index that is more valuable and informative in determining house price change.

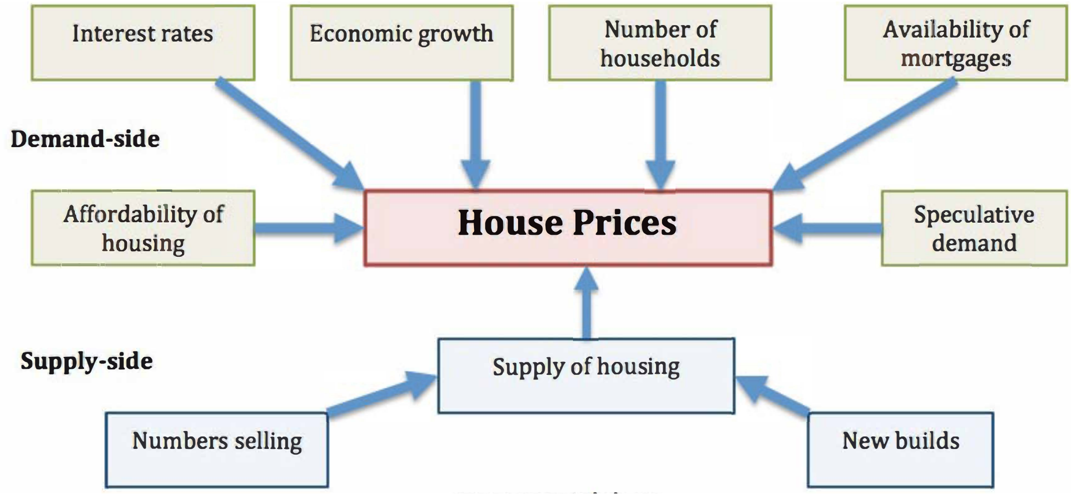
In summary, we are aiming at answering the following research questions:

1. Whether and to what extent does consumer sentiment affect house price, when other economic variables are controlled for?

2. How does consumer sentiment within different income, age and region subgroups work differently on house price?

3. How does consumer sentiment work differently for different house price tiers?

Figure 4.1
Factors Determining House Price



4. Can we construct a housing specific sentiment index from survey data? Will it work better in explaining house price change?

Through thorough data analyses and novel approaches, we can better understand the nature of the relationship between sentiment and house price. We believe our findings will provide valuable insights to both researchers and practitioners.

4.2 Literature

4.2.1 Determinants of House Price

As we discussed before, house price is determined by the demand and supply factors. Higher demand and lower supply lead to higher house price.

Tejvan Pettinger summarised the factors determining house price in Figure 4.1.

In this sub-section, we discuss the major findings on the determinants of the housing market. We will focus on the roles of economic variables. We first discuss intuitively whether and how it affects the demand or the supply side of the housing market, then list the findings in literature.

gross domestic product (GDP)

Not surprisingly, GDP is an important determinant of home price, because it is associated with income. Higher GDP leads to higher purchasing ability, which leads to higher house price. Therefore, there is positive relationship between GDP and house price. The strong relationship between GDP and home price has been widely studied in literature.

The strong relationship between GDP, income and the housing market has been examined in the literature. Iacoviello and Neri (2008) examine the response of GDP to housing market fluctuations and Mikhed and Zemcik (2009) concluded that in USA a decline in home prices affected negatively the consumption and GDP. Adams and Fss (2010) noticed that the GDP growth has an increasing impact on the housing market. Tsatsaronis and Zhu (2004) using data from 17 industrialized countries and through variance decomposition concluded that the long-term contribution of GDP doesn't exceed the 10% of the total variation of housing price. Many studies (Davis and Heathcote, 2003; Goodhart and Hofmann, 2008; Madsen, 2012) agree that a strong short-term relationship exist between housing market and GDP. However Madsen (2012) indicates that in the long term this nexus becomes weak. Turning on the Greek economy, Merikas et al (2010) found a bidirectional causality with a strong impact of housing investment on the economy growth.

Inflation

The relationship of inflation and house price is complicated. On one hand, while the real house value might stay the same, the "face value" of the house increases as the inflation rate increases. On the contrary, inflation may lead to lower purchasing power and lower house price. At the same time, indirectly, when inflation increases, interest rates tend to increase with it. This increases mortgage and reduces demand and hence lowers house price. Yet on the other hand, some people think buying a house is a good investment in the time of high inflation. Therefore, higher inflation also leads to the increase in demand and house price.

On the supplier side, when inflation rates rise, the cost of building new homes does too, resulting in less new constructions and therefore reducing the supply of homes, which in turn will push up the prices of existing homes.

In summary, inflation has mixed effects on house price. Empirically, there has always been a strong correlation between inflation and house prices, usually resulting in them rising.

Kearl (1979) examined the inflationary environment and concluded that in the case of false anticipation relative housing prices are affected. Similarly, Follain (1981) and Feldstein (1992) infer this negative effect of inflation on demand and on housing investments while Andrews (2010) detect upward trends of housing prices after change of inflation in both directions. On the other hand, Nielsen and Sorensen (1994) find that an increasing inflation generates housing investment motives because of the decreasing real user cost after taxes. All in all, there are discordant views concerning the actual effect of inflation on housing market (Manchester, 1987; Berkovec and Fullerton, 1989; Madsen, 2012; Apergis and Rezitis, 2003; Tsatsaronis and Zhu, 2004; Bork and Muller, 2012).

Interest Rate

The interest rate is related to the mortgage rate, which determines the monthly repayment amount when one buys a house. Therefore, the higher the interest rate, the less affordable the house becomes, the lower the demand, and finally the lower the house price. Meanwhile, the higher the interest, the more willingly people want to save money, which also leads to lower demand and lower house price. However, conversely, a decline in interest rates is usually accompanied by an increase in inflation, which also leads to lower purchasing power and lower house price in the long run. In summary, interest rate has a mixed effect on house price. However, researchers find that the relationship between interest rate and house price is often negative.

When the interest rate is rising, the cost of borrowing is also rising and the potential buyers are getting discouraged. As a result housing demand is falling. On the contrary, when the interest rates are on the decrease, e.g. because of money supply growth, then the user cost of housing is going down and the demand for housing is rising (Apergis and Rezitis, 2003; Igan et al, 2011). Andrews (2010) argues that the correlation between house prices and the loan interest rate is negative and depends on the degree of competition in the banking sector.Frederic (2007) detects six direct and indirect ways in which the rate is affecting the housing market:

directly on the user cost of capital, on the expectations for the future movements of prices and on the housing supply; indirectly through housing wealth changes and credit-channel effects on consumption and on demand. Jud and Winkler (2002) and Painter and Redfearn (2002) argue that the influence of houses prices on interest rates is of minor importance while others that the interest rate is one of the most crucial macroeconomic factors of housing (Tsatsaronis and Zhu, 2004; Assenmacher-Wesche and Gerlach, 2008; Iacoviello, 2005; Iacoviello and Pavan, 2011; Goodhart and Hofmann, 2008; Zan and Wang, 2012).

Unemployment Rate

Obviously, unemployment rate is also an important determinant of house price. The higher the unemployment rate, the less the number of people who can afford a house, which leads to less demand and lower house price. Therefore, the relationship between unemployment rate and house price is clearly negative.

Employment and household income are important factors (see Lerbs 2011; Giussani et al, 1992; Baffoe-Bonnie, 1998). Smith and Tesarek (1991) examined the effect of a real estate activity decrease and found that the latter leads to a decreased employment growth rate. Schnure (2005) concludes that an unemployment rate percentage increase of one unit leads to housing price decrease of 1%. Blanchflower and Oswald (2013) and Oswald (1999) connect the labour mobility and the home ownership rate and find evidence of negative externalities of the housing market on the labour market. They argue that a home-ownership rate increase affects labour mobility and leads to an unemployment rise.

4.2.2 Effects of Consumer Sentiment

When consumer sentiment index was first constructed in the 1950s, the initial goal was to better predicting durable expenditures. Therefore, not surprisingly, the majority of the literature on consumer confidence have focused on its implications and predictive powers on expenditures and other related economic or financial variables.

Okun (1960) studied the value of ICS in forecasting National Product from cross-section data. He decomposed the index to the attitude component and the buying plan component, and concluded that attitude other than buying plan was not significant in predicting National Product. On the other hand, Mueller (1963) reached the opposite conclusion. By analysing the quarterly ICS data from 1952 to 1961 by time series regression, he concluded that attitude contains unique information in terms of forecasting spending. Similarly, Adams (1964) also supported this view. By examining the disintegrated information from ICS, he concluded that attitudes make a significant contribution in forecasting durable expenditures, while the expected business condition in short-term component is the most important one. However, when more variables were considered, the conclusion seemed to be questionable again. in the previous studies, only a couple of control variables were included in the model, sometimes disposable income alone. Friend and Adams (1964) added stock prices and other non-attitudinal variables to the regression model, and found that stock prices and non-attitudinal variables such as the length of the work week, share the predictive ability of consumer attitude. Juster et al. (1972) expended the findings to nondurables. They found that consumer attitude not only was of significance in forecasting models for durable spendings, but interestingly, also explained expenditures on nondurables.

Garner (1991) argued that confidence surveys were seldom useful in forecasting economic performance, except for exceptional instances such as the Gulf War. Throop (1992) agreed with this argument. He had a thorough study on the effects of consumer sentiment by applying new methods such as vector error correction to avoid spurious regression results. He found out that sentiment change caused spending change. However, sentiment did not have much predictive power on spending, as it generally did not provide additional information. But at times of an unusual event, it did provide unique information.

Fuhrer (1993) applied VAR model to study the role consumer sentiment plays in the US macroeconomy, and he concluded that its forecasting value is statistical, but not economic significant. Similarly, Emerson and Hendry (1994) used the VAR technique to show that in general, leading indicators do not have any additional information in forecasting. Oppositely, Acemoglu and Scott (1994) analysed UK data on consumer confidence by VAR model, Granger Causality test and exclusion tests, and reached the conclusion that confidence is useful in predicting consumption. They were also a supporter of the precautionary effect view on consumer confidence.

In addition to consumer spending, researchers also studied consumer confidence's effects on other variables, such as stock price, unemployment rate, etc. In particular, Leeper (1992) studied the predictive power of consumer confidence on industrial production and unemployment. He separated the confidence index to two parts: one corresponds to economic information, and one corresponds to non-economic events, and studied the role of the second part of confidence index on the two dependent variables, industrial production and unemployment in a VAR model. He concluded that confidence index did not have predictive value when other variables were added to the model. On the other hand, Matsusaka and Sbordone (1995) found that confidence granger caused GNP change. David Gulley and Sultan (1998) studied the effect of consumer confidence on the financial market using a GARCH model, and concluded that consumer confidence only influences the Dow Jones Industrial Average, but not bond or other stock indexes.

Previous studies were almost always based on ICS, researchers started to pay attention to other consumer confidence indexes, and some comparisons between indexes became available. Huth et al. (1994) compared the performance of ICS and CCI in forecasting expenditures, business activities and economic activities, and concluded that while they were both useful, ICS outperforms CCI when predicting durable expenditures, whereas the reverse is true for general economic activity. Bram and Ludvigson (1998) also compared the predictive power of ICS and CCI. In addition to the indexes, they also compared the expectation components, and broader sentiment measures. They concluded that CCI and CCI's expectation component have a better predictive power on more categories of household expenditures, except for automobile expenditures. Lovell and Tien (1999a) compared ICS with Economic Discomfort Index (EDI), which was defined as unemployment plus annual rate of inflation. They concluded that EDI contains similar information to ICS. Lemmon and Portniaguina (2006) studied the relationship between consumer confidence and asset prices, by using consumer confidence as a measure of investor optimism. They rejected sentiment's prediction value. On the other hand, Bollen et al. (2011) found that sentiment that is implied by Twitter mood predicts the stock market.

Some researchers further processed the consumer confidence data. Desroches and Gosselin (2002) studied the usefulness of consumer confidence indexes. The uniqueness of their work is that they claim only large variations of confidence can affect spending. By analysing the filtered data using a threshold, they observed that "consumer confidence is a statistically important determinant of consumption in periods of high uncertainty". Souleles (2004) the first to use micro data (household data) underlying ICS to study its relationship with consumption. He found that the results change with time, and group of households. He also reported results that were consistent with precautionary motives, which contradicts the results from several macro level studies Chatterjee and Dinda (2015). Michis (2010) claimed that the denoised ICS can forecast GDP efficiently.

In summary, while most researchers agree that sentiment and economic output (such as consumer expenditures, stock returns, and GNP) are positively correlated (Berry and Davey, 2004; Friend and Adams, 1964; Fuhrer, 1993; Jansen and Nahuis, 2003; Leone and Kamakura, 1983; Matsusaka and Sbordone, 1995; Throop, 1992), there is disagreement on whether this is merely because they are determined by the same economic variables, or sentiment is indeed an independent variable with some predictive power.

The discrepancy in the results is mainly due to different control variables and different data analysis approaches. Recent studies have applied more econometric tools (such as the Granger causality test, in-sample and out-of-sample analyses) or further examine the data (for example, utilising household-level demographic data or individual answers gathered from the questionnaire) to avoid spurious results. However, the literature still offers conflicting evidence. Hence, more research effort is needed to better interpreting the effects of sentiment.

4.2.3 Sentiment's role on House Price and House Price Volatility

When consumer sentiment's role is studied, more focus has been given to its role on the stock market and other financial markets. On the other hand, the research in the determinants of housing market performance gives more weight to the roles of economic variables and other factors. However, there are still some papers that study the relationship between consumer sentiment and the housing market.

The paper that is most closely related to our focus is Ling et al. (2015). This paper used a VAR model to study the effect of sentiment on house price. It considered "sentiment" of three major agents in the U.S. housing market: potential home buyers, home builders, and residential mortgage lenders. It found that all three types of sentiment had a positive effect on house price.

In the paper, the authors constructed a consumer sentiment measure, based on the answer to one question from the University of Michigan Survey of Consumers. They also used answers to one question in Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices as a proxy for lender sentiment.

After obtaining the sentiment measures, these survey-based sentiment measures are orthogonalised against a wide range of fundamental variable. And then, a composite sentiment index is constructed by taking the first principal component of the three orthogonalised indices. They also included another variable, a proxy for market liquidity, in the model. They analysed the VAR model and did various robustness tests.

The limitations of the paper include the following: since lenders' sentiment data were only quarterly available, the authors convert all other monthly data to quarterly one, by using March, June, Sept, and Dec's data. There were barely 82 data points. A lot of information might have been lost due to this data processing approach, since we all know sentiment data and house price data fluctuate frequently.

This paper inspired our Hypothesis 4. And we make our own contributions by considering another important agents' sentiment; constructing a much better housing specific consumer sentiment; and providing a thorough comparison within income/house-price tiers, age subgroups and regions.

Another piece of literature that is closely linked with our focus is Johnson (2010). In Chapter 3 of his Thesis, Johnson (2010) used a VAR model to study the effect of consumer sentiment on home prices and home sales. It found that consumer sentiment does impact home prices and home sales. It also compared the results for different age groups. And also used a panel VAR model to take regional difference into consideration.

Four variables were considered in his VAR equation: consumer confidence (either national, or age group specific), house price, house sales, and 30 year conventional mortgage rate (newly included). He used Granger causality results to find the directions of the relationships. he found that sentiment did affect home price and home sales.

In his model, no or just one control variable was included. The VAR model was extremely simple. Hence, It could not rule out the possibility that other major microeconomic variables (which influence ICS) were causing this relationship. In addition, It did not compare or discuss regional difference. Moreover, some interpretations of the results were not very convincing.

Clayton et al. (2009) investigated the role of fundamentals and investor sentiment in commercial real estate valuation. In real estate markets, heterogeneous properties trade in illiquid, highly segmented and informationally inefficient local markets. Moreover, the inability to short sell private real estate restricts the ability of sophisticated traders to enter the market and eliminate mispricing. These characteristics would seem to render private real estate markets highly susceptible to sentiment-induced mispricing. Using error correction models to carefully model potential lags in the adjustment process, this paper extends previous work on cap rate dynamics by examining the extent to which fundamentals and investor sentiment help to explain the time-series variation in national-level cap rates. We find evidence that investor sentiment impacts pricing, even after controlling for changes in expected rental growth, equity risk premiums, T-bond yields, and lagged adjustments from long run equilibrium.

On the contrary, Dua (2008) analysed the determinants of consumers' perceptions of buying conditions for houses. He used the answer to one question from the University of Michigan Survey of Consumers as a proxy for measuring consumers' home buying perceptions. He then found that variables such as house prices, mortgage rates, wealth, employment and income levels have an impact on consumers' attitudes, by using a VAR model. In other words, in his research, house buying specific consumer sentiment is the dependent variable, and the economic variables are the determinants.

4.3 Data

In this section, we list the sources or constructions of all the variables that will be used in our data analyses. We also explain why we make these choices. In additional, we plot these series, and make some initial observations. Finally, we list their summary of statistics.

4.3.1 Consumer, Builder, Lender and Realtor Sentiment

Sentiment of Consumers (ICS)

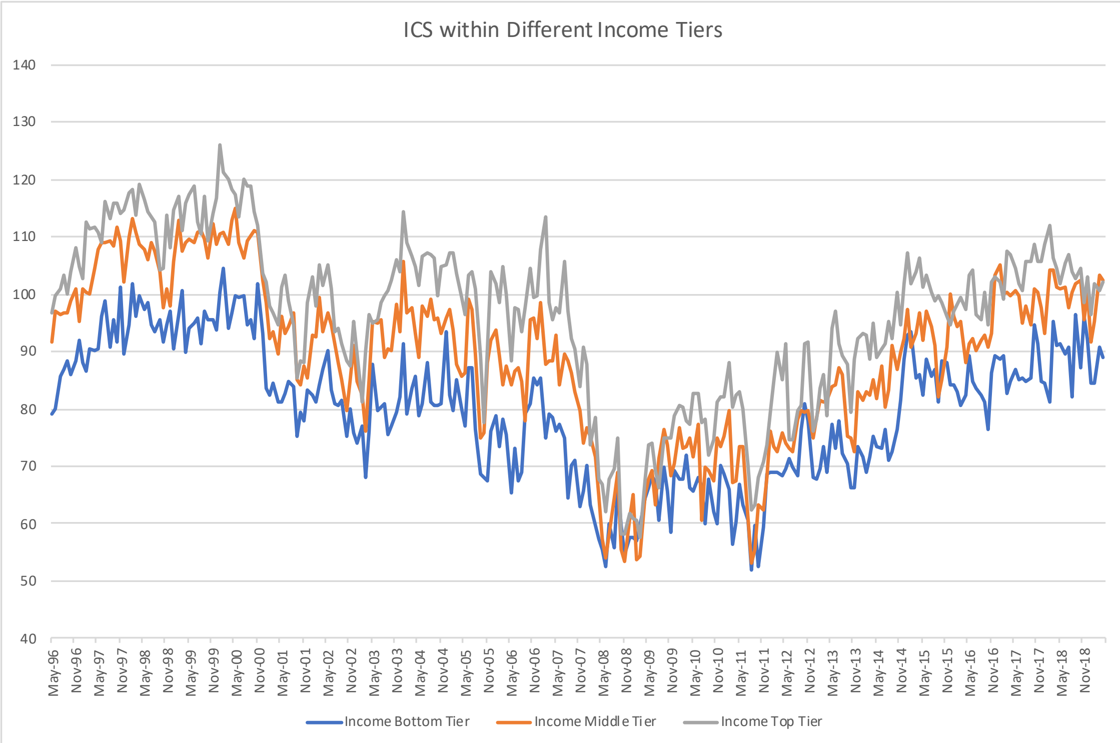
The survey results from the Survey of Consumers by University of Michigan are used in this study. In particular, Consumer Sentiment Index (ICS) is used as a proxy for US consumer sentiment. In Chapter 1, we have already explained in detail how ICS is constructed and calculated from five survey questions. Here, we discuss the reasons why we only focus on this index:

Firstly, ICS is the most widely used proxy for consumer confidence in literature. It is the first survey based index that aims at measuring consumer confidence, and has been proven useful in serving this goal.

Secondly, it has a pretty long time range. The monthly data are available from as early as 1978. The more than 40 years of monthly data allow us to study the relationship between sentiment and house price in the long run. The only other index that measures sentiment/confidence that has a similar time range is the Conference Board's Consumer Confidence Index. There is another sentiment index that is specifically designed for the housing market, The Home Purchase Sentiment Index by Fannie Mae. However, that series only provides data for the last ten years.

Lastly, all the survey results from the Survey of Consumers are freely accessible. Not only the result of each single survey question, but also the answers by demographic subgroups, are available for download. This gives us freedom to dig into the survey answers and extract more information. In particular, we are interested

Figure 4.2
ICS within different income tiers



in comparing the roles of ICS within different age groups, income tiers, and regions. Fortunately, ICS within three income tiers (top, middle and bottom), three age groups (34 and below, 35 to 54, and 55 and above), and four regions (East, West, North East, and Midwest), are all available. Their graphs are shown in Figures 4.2, 4.3 and 4.4. We can observe that people with higher income tends to have higher sentiment than people with lower income. Similarly, younger people tends to have higher sentiment than older people. On the other hand, ICS within different regions are quite easily comparable.

Sentiment of Builders (IBS)

We use the NAHB/Wells Fargo Housing Market Index as a proxy for builders' sentiment. This index is based on a monthly survey of NAHB (i.e, National Association of Home Builders) members designed to take the pulse of the single-family housing market. The survey asks respondents to rate market conditions for the sale of new homes at the present time and in the next six months as well as the traffic of

Figure 4.3
ICS within different age subgroups

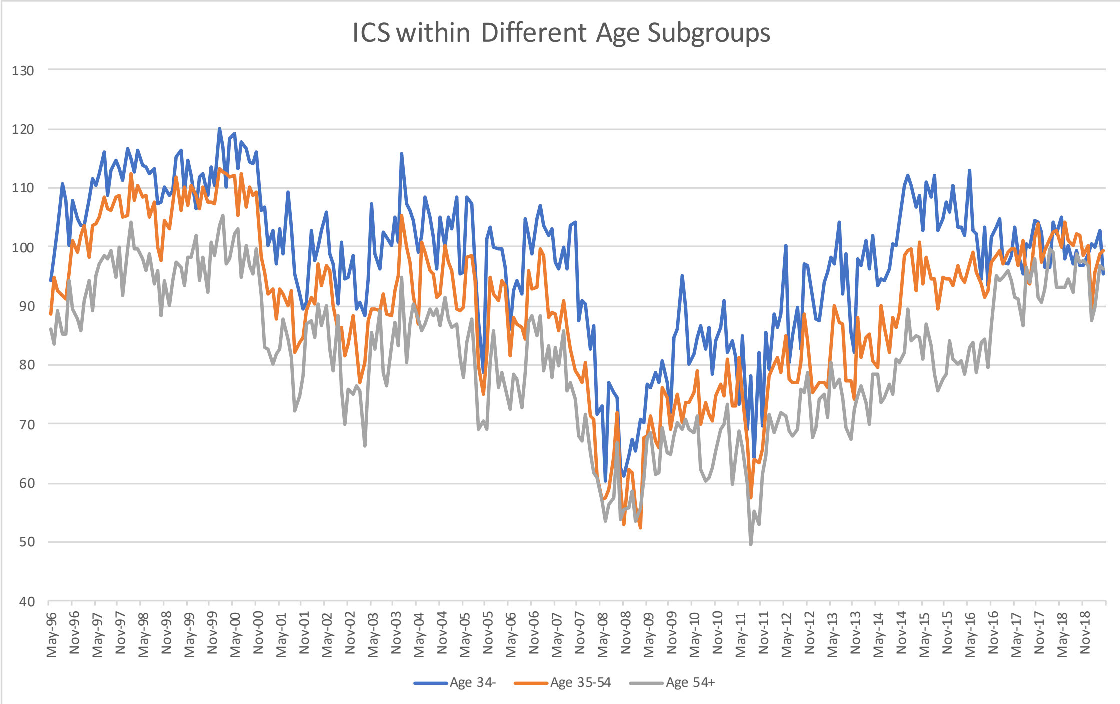
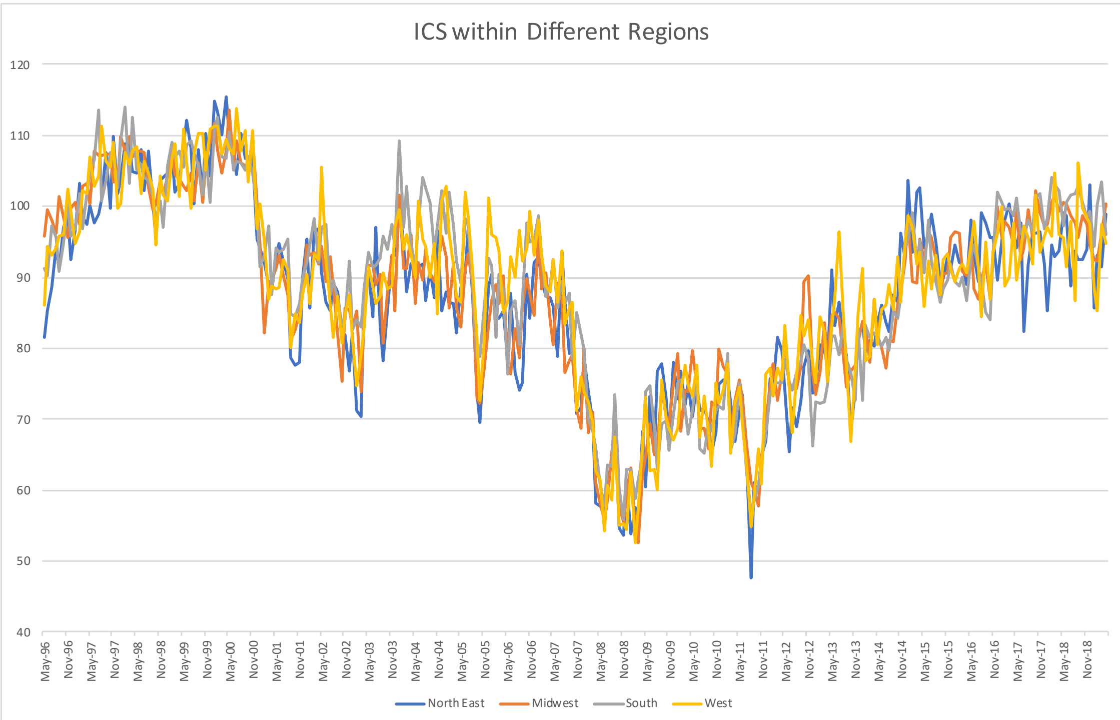


Figure 4.4
ICS within different regions



prospective buyers of new homes. It is monthly available since 1985.

Sentiment of Realtors (IRS)

We use NAR's Realtors Confidence Index (6-month outlook) as a proxy for real state agents' sentiment. National Association of Realtors (NAR) send monthly survey to over 50,000 real estate practitioners. Practitioners are asked about their expectations for home sales, prices and market conditions. Realtors Confidence Index (6-month outlook) is based on their answers to a particular question in the survey, and is a good representation of realtors' sentiment on housing market strength. The index is monthly available since 2008.

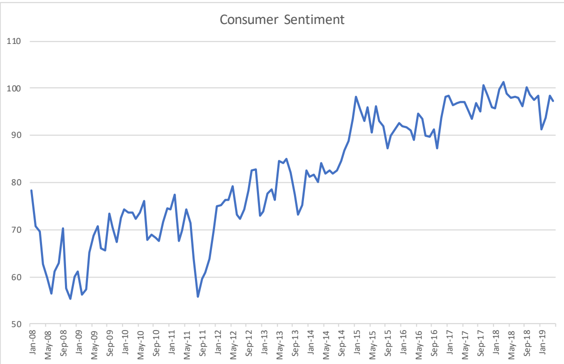
Sentiment of Lenders (ILS)

To estimate lenders' sentiment, we follow the approach in Ling et al. (2015). We estimate the lenders' sentiment from one survey question in Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. The survey is conducted quarterly, and questions cover changes in the standards and terms of the banks' lending and the state of business and household demand for loans. The particular question we focus on is: "Over the past 3 months, how have your bank's credit standards for approving applications from individuals for mortgage loans to purchase homes changed?" We calculate the net percentage of positive answers, i.e, the percentage answered "eased somewhat" or "eased considerably" minus percentage answered "tightened considerably" or "tightened somewhat". In words, this net percentage shows how easy the home purchase mortgage application is getting approved. Clearly, it is a good indication for lenders' sentiment. The data is quarterly available since 1997. We convert it to monthly data by assuming the same index applies for all the 3 months in that quarter.

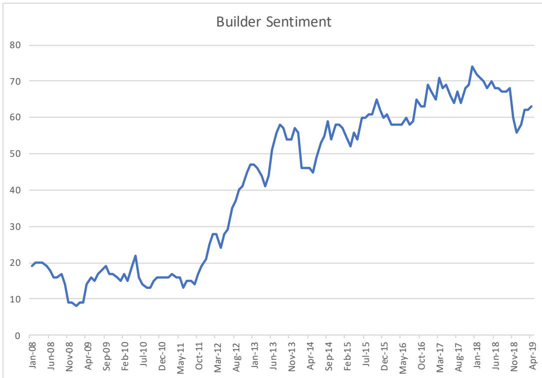
The Consumers', Builders', Realtors' and Lenders' sentiment indices from 2008 to now are shown in Figure 4.5. We can clearly see that they share some similarities (in general, sentiment has an increasing trend since 2008), but each series also has some uniqueness.

Figure 4.5
Consumers', Builders', Realtors' and Lenders' sentiment

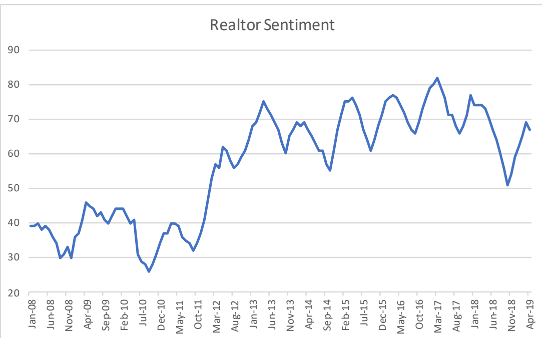
(a) Consumer Sentiment (ICS)



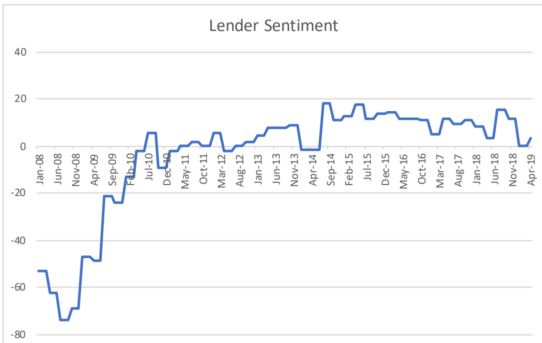
(b) Builder Sentiment (IBS)



(c) Realtor Sentiment (IRS)



(d) Lender Sentiment (ILS)



4.3.2 House Price

There are several widely used US house price indices. For example, the US Federal Housing Finance Agency publishes the HPI index, a quarterly broad measure of the movement of single-family house prices. On the other hand, The Case-Shiller house price index is monthly available, but has a long lag time (2 months). They are both based on weighted-repeat sales methodology (see Case and Shiller (1988)).

However, we choose Zillow Home Value Index (ZHVI) as the proxy for house price in our study. The advantage of ZHVI is that it overcomes a major problem in existing indices: their inability to deal with the changing composition of properties sold in one time period versus another time period. Both a median sale price index and a repeat sales index are vulnerable to such biases. The other reasons why we choose this index are as follows:

Firstly, ZHVI is widely recognised in literature. Secondly, it also has a pretty long time range. It is monthly available since 1996, which gives us more than 270 data points.

Lastly, in additional to the general ZHVI, Zillow also divides the house values to three price tiers (top, middle or bottom tier), and provides us with tier specific ZHVI's. The thresholds for the price tiers vary from metro to metro and are determined by the distribution of home values in each metro. We think it is interesting to compare sentiment's role in the top price tier versus in the bottom one. ZHVI allows us to do this comparing analysis easily.

The general ZHVI, as well as the Top and Bottom Tiered ZHVI data are shown in Figure 4.6. We can see that the price indices have a similar increasing trend. Their percentage change are shown in Figure 4.7. It clearly shows that although the percentage change of the top-tiered price and the percentage change of the bottom-tiered price share a similar trend, the latter seems to have bigger volatility, especially in certain periods.

In Figure 4.8, we rescaled the ICS and the percentage change in ZHVI data to [0, 1], and plot the new time series on the same graph. The plot clearly shows that ICS and ZHVI move in a very similar trend. It is consistent with our hypothesis. However, it is hard to tell directly the change of which leads to the change of

Figure 4.6
House Price Index, ZHVI (General/Top-Tier/Bottom-Tier)

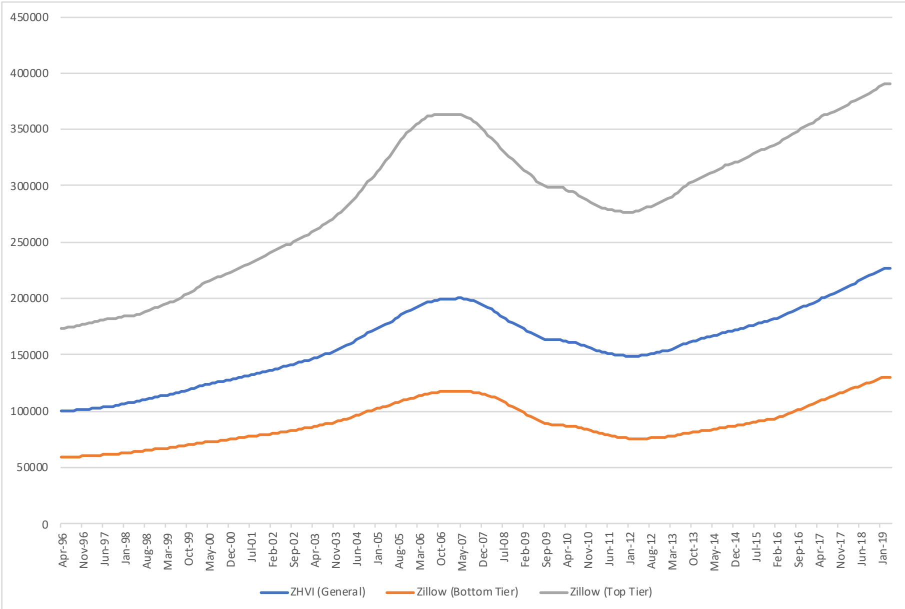


Figure 4.7
Percentage Change in House Price Index, ZHVI (General/Top-Tier/Bottom-Tier)

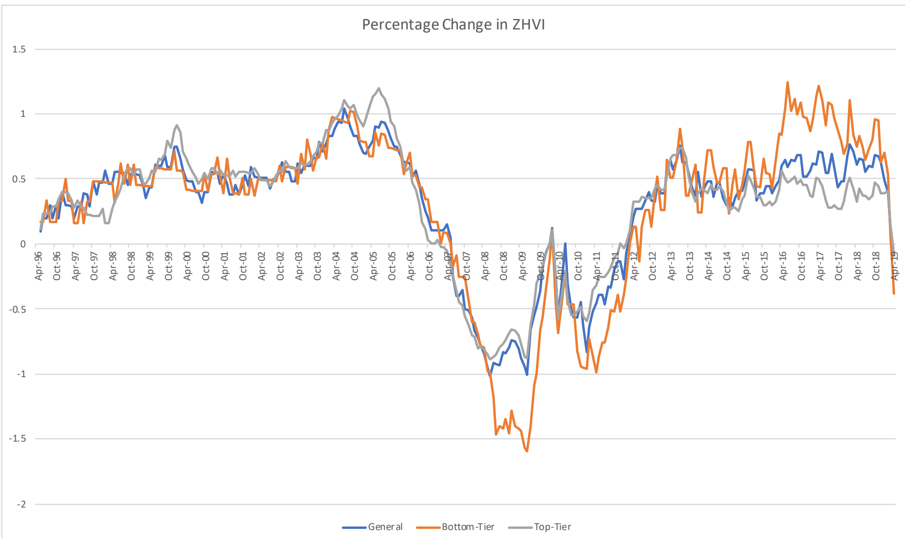
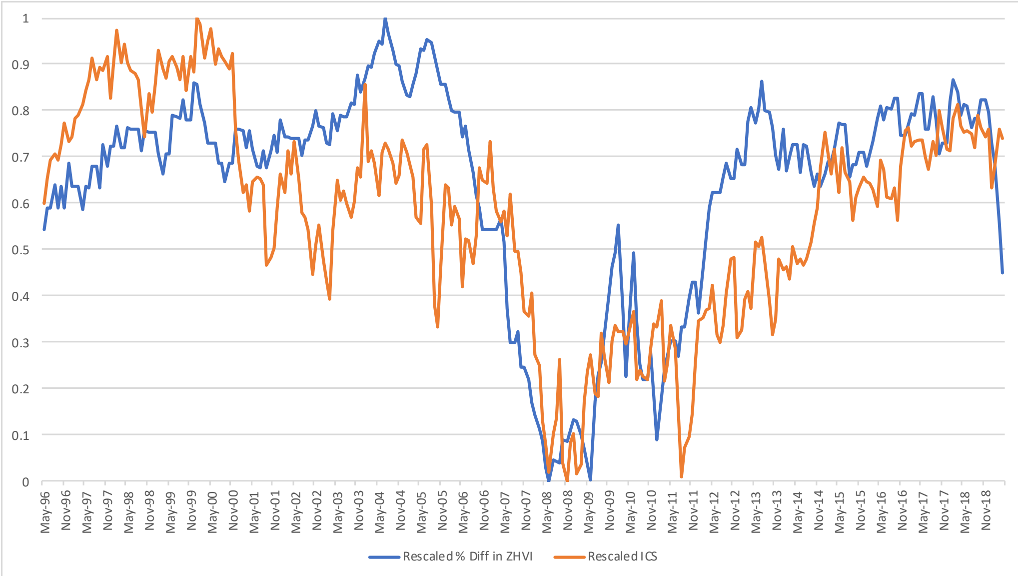


Figure 4.8
Rescaled ICS and Percentage Change in ZHVI



the other. Hence, a thorough data analysis is needed to further examine their relationship.

4.3.3 Control Variables

As discussed in the Literature Review section, we understand that interest rate, unemployment rate, change in GDP, and inflation are all important determinants of home price. Therefore, we include these four microeconomic variables as control variables in our model. All these variables are downloadable from Datastream and the Federal Reserve Bank of St. Louis (`fred.stlouisfed.org`).

- Industrial Production Index (IPI): monthly data that measures the real production output of manufacturing, mining, and utilities. It can be used as a proxy for gross domestic product (GDP), which is only available quarterly.
- Consumer Price Index (CPI): monthly data that measures changes in the price level of a market basket of consumer goods and services purchased by households. Its first difference denotes inflation rate (INF).
- Interest Rate (INT): monthly data of the 3-Month Treasury Bill Rate.

- Unemployment Rate (UNE): monthly data that measures percentage in labour force that are unemployed.

Similar to what we discussed in Chapter 1, we process these data first, based on the meanings of the variables, and stationarity test results. Our decisions are as follows: for IPI, its percentage difference is used. We should note that this is very similar to its first differences in its logged values, which was what we used in Chapter 1. For CPI, we take the first differences. In other words, inflation rate INF is used. For the other two variables, INT and UNE, we just use the levels of these variables directly.

We plot the time series for all the processed control variables in Figure 4.9. We can see that the processed series do not seem to be autocorrelated, have a monotonic trend, or be nonstationary. Compared this figure with Figure 4.8, we can clearly see that each control variable follow unique moving trend. Unlike ICS, their trends are quite distinct with the moving trend of the percentage change in ZHVI. However, it is still possible that a linear combination of these control variables explains the large part of the percentage change in ZHVI. It is still worth including these control variables in our model, and study the extra explanatory power of ICS.

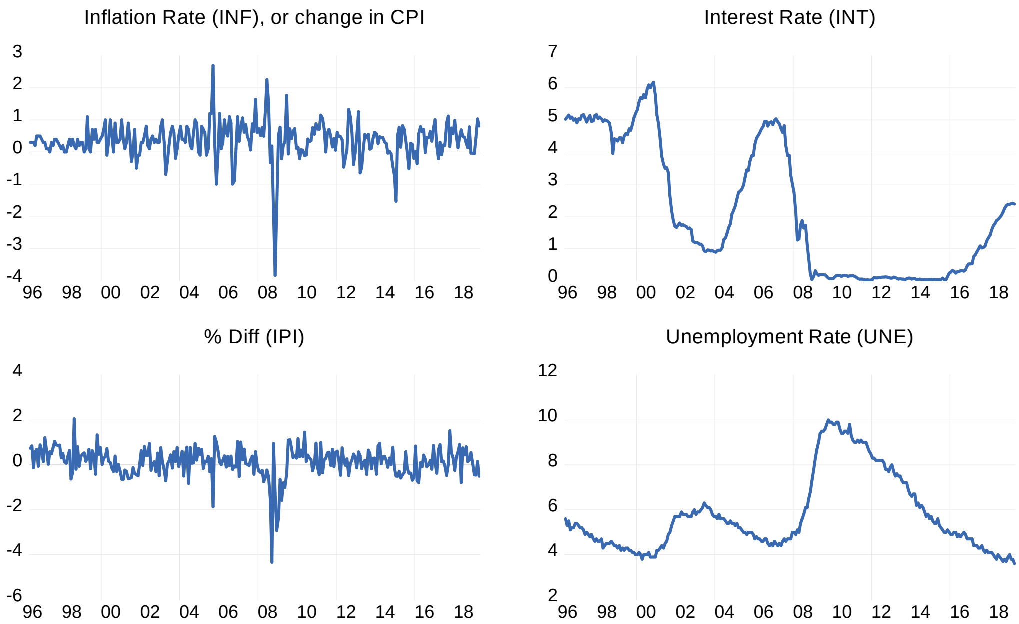
In summary, our basic model includes the following variables:

- Dependent variable: percentage difference in ZHVI. To simplify the notation, we will denoted as ΔZHVI.
- Main independent variable: ICS.
- Control variables: INF (i.e., ΔCPI), percentage difference in IPI (denoted as ΔIPI), INT, and UNE.

Summary Statistics

The summary statistics for all these series for the time period May 1996 to Apr 2019 (IRS is only available from Jan 2008) are reported in Table 4.1. We can see that difference sentiment indices have different ranges, due to different constructions calculation methods. For example, The builders' sentiment ranges from 8 to 78,

Figure 4.9
Time Series for all the Control Variables



while the lenders' sentiment ranges from -74 to 18.3. The landers' sentiment also has high Kurtosis value, indicating the data has heavy tails. For the control variables, the percentage change in IPI also has a very high Kurtosis value, indicating that there are "outliers". Other data have much lower Kurtosis values.

We can also observe the range of ΔZHVI is from -1.02 to +1.04. The lowest value (meaning the biggest percentage drop in house price between the current month and the previous one) happens in June, 2008, around the start of the 2008 Financial Crisis. The highest value (meaning the biggest percentage increas in house price between the current month and the previous one) happened in July 2004. On the other hand, ICS ranges from 55.3 to 112. The smallest value takes place in Nov 2008, during the 2008 Financial Crisis. The largest value takes place in Jan 2000.

4.4 Methodology

4.4.1 Basic Model

Our objective is to test our hypotheses 1, 2(a), 2(b), 2(c) and 3. In other words, We aim at examining the relationship between consumer sentiment (overall or within a

Table 4.1
Summary Statistics

	ΔZHVI	ICS	IBS	ILS	IRS	ΔIPI	INF	INT	UNE
Mean	0.30	88.19	50.32	-2.84	56.58	0.36	0.13	2.14	5.76
Median	0.46	90.95	58.00	0.00	61.00	0.39	0.17	1.58	5.20
Maximum	1.04	112.00	78.00	18.30	82.00	2.70	2.05	6.17	10.00
Minimum	-1.02	55.30	8.00	-74.00	26.00	-3.84	-4.34	0.01	3.60
Std. Dev.	0.47	13.08	19.73	17.56	15.76	0.57	0.65	2.04	1.71
Skewness	-1.23	-0.49	-0.81	-2.37	-0.35	-1.56	-1.73	0.48	1.09
Kurtosis	3.57	2.58	2.22	8.75	1.69	15.21	12.23	1.64	3.05
Observations	276	276	276	276	136	276	276	276	276

Note: ΔZHVI = percentage change in Zillow Home Value Index. ICS = Index of Consumer Sentiment for US by University of Michigan. IBS = Index of Builder Sentiment. ILS = Index of Lender Sentiment. IRS = Index of Realtor Sentiment. ΔIPI = percentage change in Industrial Production Index. INF = inflation rate, or first difference of Consumer Price Index (CPI). INT = 3-Month interest rate. UNE = unemployment rate. All are monthly data from May 1996 to April 2019, except for IRS, which is from Jan 2008.

subgroup) and house price change (overall or within a price-tier). In this section, we explain the complete data analysis procedure we shall take in search for the empirical evidence, which includes calculation of correlation, regression analysis, and Vector Autoregression (VAR) model analysis. Under the VAR model, we performed granger causality tests, impulse response analysis, and variance decomposition. Our choices of approaches were based on the characteristics of the data and the existing literature. The approach is identical to the one we used in Chapter 1.

Clearly, based on our objective, the two main variables we study are ICS (consumer sentiment, either overall or within a subgroup) and ΔZHVI (percentage change in house price, either overall or within a price-tier). In order to eliminate the possibility that the effect of ICS on ΔZHVI is already covered by other economic variables, we also need to include a set of control variables (CONTROLS = {ΔIPI, INF, INT, UNE}) in our model.

Correlation

We first calculate the correlation matrix for all the variables (ICS, ΔZHVI CONTROLS). We are especially interested in the correlation between two main variables, corr(ICS, ΔZHVI). Based on Hypothesis 1, we expect their correlation to be large and significantly positive. Moreover, based on Hypotheses 2(a), 2(b), 2(c) and 3, we expect their correlation to be slightly different for different subgroups of data.

The correlation does not tell us the relationship between lagged values of the variables, hence can not provide any causality information. Nor can it tell us the extra explanatory power of ICS on ΔZHVI given CONTROLS. Therefore, at the next step, we move to a regression model.

Regression Model

We then focus on the following regression model in Equation 4.4.1. In the equation, t denotes the time period (monthly), and T^* denotes the optimal number of lags according to Akaike information criterion (with maximal number of lags for consideration being 10).

$$\Delta\text{ZHVI}_t = \alpha + \sum_{i=1}^{T^*} \beta_i \text{ICS}_{t-i} + \gamma\text{CONTROL}_{t-1} + \epsilon \tag{4.4.1}$$

We are interested in the sign of the coefficients of the lagged values of ICS, or $\sum_{i=1}^{T^*} \beta_i$. We expect it to be positive and significant. We are also interested in the (extra) explanatory power of ICS. To do this, we further consider the following two regression equations:

$$\Delta\text{ZHVI}_t = \alpha + \gamma\text{CONTROL}_{t-1} + \epsilon \tag{4.4.2}$$

$$\Delta\text{ZHVI}_t = \alpha + \sum_{i=1}^{T^*} \beta_i \text{ICS}_{t-i} + \epsilon \tag{4.4.3}$$

We will calculate the change in adj-R^2 from Model 4.4.2 to Model 4.4.1, and this value shows the extra explanatory power of ICS on ΔZHVI. We will also record adj-R^2 of Model 4.4.3, which implies how much variance of ΔZHVI can ICS alone explain.

The regression models help us test our hypothesis in several angles. It verifies the sign of the relationship between ΔZHVI and lagged values of ICS. Furthermore, it not only checks the explanatory power of ICS on ΔZHVI, but also checks its extra explanatory power when CONTROLS are included in the model. However, there are several limitations: firstly, they suffer from autocorrelation problem. Secondly, they do not tell us whether the relationship is causal. Thirdly, they do not allow us to check when there is a shock in ICS, how ΔZHVI would respond to it. These limitations can be overcome by a vector autoregression model. Therefore, we proceed to the vector autoregression model.

Vector Autoregression (VAR) Model

Our VAR model is similar to the regression model. We regard all variables (ΔZHVI, ICS and CONTROLS) as endogenous variables. The model has the following format:

$$Y_t = A_0 + \sum_{i=1}^{T^*} A_i Y_{t-i} + u_t,$$

where Y_t denotes the endogenous variable vector, u_t denotes the error vector that satisfies certain criteria, A_i denotes the coefficient vector, and T^* denotes the optimal number of lags. In particular, we consider the following three models: Model (1): $Y = \{\Delta\text{ZHVI}, \text{ICS}, \text{CONTROLS}\}$. Model (2): $Y = \{\Delta\text{ZHVI}, \text{CONTROLS}\}$. And Model (3): $Y = \{\Delta\text{ZHVI}, \text{CONTROLS}\}$. Under the VAR model, we first record coefficient and adj-R^2 values just as in the regression model.

Once we have estimated a VAR model, we are also able to analyse its properties using structural analysis, which includes three interdependent approaches. The first approach is the Granger causality test. We do both pairwise Granger causality test between the main variables, and Granger causality test for the complete model (with control variables). In particular, to test whether ICS pairwise Granger causes ΔZHVI, we consider the following model:

$$\Delta\text{ZHVI}_t = a_0(1) + \sum_{i=1}^{T^*} a_i(1,1) y_{t-i} + \sum_{i=1}^{T^*} a_i(1,2)\text{ICS}_{t-i} + u_t(1). \tag{4.4.4}$$

And to test whether ICS Granger causesΔZHVI in the complete model, we consider the following model:

$$\Delta \text{ZHVI}_t = a_0(1)+\sum_{i=1}^{T^*} a_i(1,1)y_{t-i}+\sum_{i=1}^{T^*} a_i(1,2)\text{ICS}_{t-i}+\sum_{i=1}^{T^*} B_i(1)\text{CONTROL}_{t-i}+u_t(1). \tag{4.4.5}$$

In both cases, we test the joint hypothesis:

$$a_1(1,2) = a_2(1,2) = ... = a_{T^*}(1,2) = 0,$$

with Null hypothesis being ICS does not Granger cause ΔZHVI.

After the causality tests are done, under the VAR model, we also obtain the impulse response functions (IRF). The IRF gives the jth-period response when the system is shocked by a one-standard-deviation shock. We are interested in tracing the dynamics of ΔZHVI to a shock to ICS. We expect that a shock to ICS causes ΔZHVI to change positively temporarily.

Finally, we perform variance decomposition. While impulse response functions trace the effects of a shock to one endogenous variable on to the other variables in the VAR, variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR. Thus, the variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR. In particular, we focus on the decomposition of ΔZHVI. The variance decomposition results tell us in the short run (for example, at the 2nd month) and in the long run (say, in 60 months, or 5 years), shock to ICS accounts for how much variation of the fluctuation in ΔZHVI. We expect that part of the variance ofΔZHVI is explained by ICS.

Summary

In summary, Hypothesis 1 has several implications: the correlation between ICS and ΔZHVI should be positive. ICS should have a significant and (extra) positive explanatory power over ΔZHVI in the regression model, even when CONTROLS are included. In a VAR model containing both ICS and ΔZHVI, the former should Granger Cause the latter. The impulse response results should show a positive relationship between ICS andΔZHVI, where the former leads the latter. And finally, the variance decomposition results should show that part of the variance of ΔZHVI is explained by ICS.

Hypotheses 2(a)-(c) and Hypothesis 3 have the following implications: the positive relationship we discussed above is bigger and more significant for consumers with higher income, for middle-aged consumers, and on higher price-tiered houses. Moreover, the positive relationship we discussed above is slightly different for consumers from different regions.

4.4.2 Constructing Housing Specific Consumer Sentiment Index

As explained in Chapter 1, ICS is generated based on consumers' responses to five survey questions listed below.

Q6 = "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"

Q8 = "Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

Q28 = "Now turning to business conditions in the country as a whole–do you think that during the next twelve months we'll have good times financially, or bad times, or what?"

Q29 = "Looking ahead, which would you say is more likely–that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?"

Q35 = "About the big things people buy for their homes–such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?"

Note that the indices of the questions (such as 6, 8, 28, 29, 35) represent the actual question numbers in the survey. ICS is calculated by taking the average of the answers to these five questions.

We can clearly see that the questions are not housing market specific. However, there are actually questions on house selling/buying conditions in the same survey (University of Michigan's Survey of Consumers). These questions and some other questions could potentially be more useful in reflecting housing related sentiment. By using the replies to these questions to construct a new sentiment index, we may be able to provide a housing specific sentiment measure, that works better in explaining house price change. In short, our objective is to choose a new group of survey questions from Survey of Consumers, and construct a new "index of housing-specific consumer sentiment" (IHCS) based on consumers' responses to these questions.

In order to achieve this goal, we take several steps. Our approach is based on Cai et al. (2015), but additional steps are taken to validate the choice of questions in a more reliable way.

The first step is to pre-select some survey questions that are intuitively more related to house price. The survey includes as many as 42 questions, divided to the following 7 subgroups: "Personal Finances", "Savings and Retirement", "Economic Conditions", "Unemployment, Interest Rates, Prices, Government Expectations", "Household Durables Buying Conditions", "Vehicle Buying Conditions", and "Home Buying and Selling Conditions". Obviously some are more related to housing market than others. Also, some question answers have very similar trends. Hence, we should both consider the statistical results and the implications of the questions. Therefore, we don't want to include all the questions, but to pre-select a subgroup of questions.

Based on the discussed principal, we pre-select the following questions:

- Five questions that are used to generate ICS, including questions about personal finances (Q6 and Q8), economic conditions (Q28 and Q29), and buying conditions (Q35).

- All the 3 main questions on home buying and selling conditions, including buying conditions (Q41), selling conditions (Q43), and house value (Q45). And one extra question on "Reasons for Opinions About House Buying Conditions" (Q42).

- Two questions on unemployment (Q30) and interest rate (Q31).
- Two other questions, including news about economic conditions (Q23), and economic condition in the past (Q25).

In additional to the five questions used to generate ICS, the new questions are as follows:

Q23 = "During the last few months, have you heard of any favourable or unfavourable changes in business conditions?"

Q25 = "Would you say that at the present time business conditions are better or worse than they were a year ago?"

Q30 = "How about people out of work during the coming 12 months ?? do you think that there will be more unemployment than now, about the same, or less?"

Q31 = ""No one can say for sure, but what do you think will happen to interest rates for borrowing money during the next 12 months ?? will they go up, stay the same, or go down?"

Q41 = "Generally speaking, do you think now is a good time or bad time to buy a house?"

Q42 = "Why do you say so? (Choices include: Good time to buy : Prices won't go down; are going higher. etc)"

Q43 = "Generally speaking, do you think now is a good time or a bad time to sell a house?"

Q45 = "Do you think the current value of your home? I mean, what it would bring if you sold it today? has it increased compared with a year ago, has it decreased compared with a year ago, or has it remained about the same?"

In total, there are 13 questions that are pre-selected. The responses to these 13 questions give us 13 candidate variables, which we denote as A6, ..., A45.

The second step is to choose a subset of variables, and to calculate housing specific consumer sentiment accordingly. To do this, we do a Stepwise Regression, while ΔZHVI is the dependent variable, and all the 13 candidate variables are search regressors. We perform forward stepwise regression with $p-$value set as 0.05. It will result in a subset of variables that are accepted in the stepwise regression result. We calculate its set specific "sentiment" (denoted by IHCS_1) by taking the average value of the variables within the set. Note that the reason why we take the average of these question answers, but not the weighted average, is that this approach is consistent with how ICS is calculated.

On the other hand, in Cai et al. (2015), based on stepwise regression results and meanings of the questions, the authors chose five questions (Q6, Q30, Q31, Q41 and Q43) to calculate a housing related sentiment by taking the average value of the responses. In particular, let's denote their sentiment as IHCS_2, then $\text{IHCS}_2 =$ (A6+A30+A31+A41+A43)/5. We will also calculate this index at Step 2. Both IHCS_1 and IHCS_2 are considered as candidate proxies for IHCS.

The third step is to compare the performance of three candidate IHCS series: IHCS_1, IHCS_2, and the original ICS. We use two approaches to do so. Firstly, we compare the results of a simple regression model. In the model, ΔZHVI is the dependent variable, and one of the IHCS candidate is the only independent variable. We record the R^2 value, which implies how well the IHCS candidate is able to explain ΔZHVI.

Secondly, we do a pairwise Granger Causality Test across ΔZHVI, .IHCS_1, IHCS_2 and ICS. The sentiment variable that Granger causes other variables is preferred. Based on the regression and Granger Causality Test results, we finalise our choice.

Having obtained IHCS, we can repeat the steps in our Basic Model, and compare the results with ICS.

4.4.3 Constructing Composite Housing Sentiment Index

In the previous sections, only the consumers' opinions are considered. However, in addition to consumers (on the demand side, whose sentiment is denoted as ICS), other groups of people, such as builders (on the supply side, whose sentiment is denoted as IBS), realtors (intermediary between demand and supply sides, whose sentiment is denoted as IRS), and lenders(as credit suppliers, whose sentiment is denoted as ILS), are also directly linked with the housing market. To capture sentiment information from these different sources, in this section, we explain how to construct a composite Index of Housing Sentiment (IHS) from the four variables ICS, IBS, IRS, ILS. In other words, our objective is to combine consumers', builders', realtors' and lenders' sentiment into a single "housing sentiment index".

To do this, we apply principal component analysis (PCA) on the four variables ICS, IBS, IRS, ILS. And we use the first component of the PCA result as the composite index. The reasons why we use PCA instead of taking the average of the four variables are as follows: Different sentiment indices have different methodologies and different data ranges, which makes taking the average unfair. PCA is a useful dimension-reduction tool. By using the first component, it gives us different weights to different variables, which makes more sense. In the previous section, IHCS is calculated by taking the average of the responses to five questions. This is because the answers to the five questions have the same range, and are extremely comparable (answered by the same group of people).

Having obtained IHS, we can also repeat the steps in our Basic Model, and compare the results with ICS.

4.5 Results and Discussions

4.5.1 Relationship Between Consumer Sentiment and House Price

In this section, we follow the steps introduced in the Methodology - Basic Model section to study the role of overall ICS on ΔZHVI.

Correlation

Table 4.2
Correlation Matrices

Correlation	ΔZHVI	ICS	ΔIPI	INF	INT	UNE
ΔZHVI	1					
ICS	0.698	1				
ΔIPI	0.250	0.243	1			
INF	0.013	0.024	0.056	1		
INT	0.211	0.610	0.136	0.088	1	
UNE	-0.546	-0.760	-0.005	-0.049	-0.644	1

Note: Refer to Table 4.1 for variable notation.

Table 4.2 presents the correlations among all variables, including two main variables ICS and ΔZHVI, and four control variables. The correlation between ICS and ΔZHVI is +0.698 (with $p-$value 0.0000). As expected, it is positive and significant. This implies that when ICS increases, ΔZHVI tends to increase as well. It is consistent with our Hypothesis 1. We can also observe that unemployment rate is negatively correlated with ΔZHVI, while interest rate is positively correlated with ΔZHVI. On the other hand, the correlation between inflation rate and ΔZHVI is insignificant. These are consistent with what we discussed in the Literature Review section.

Here we provide two possible explanations for the positive correlation:

1. ICS reflects current economic conditions, and the current economic conditions influence ΔZHVI.

2. ICS contains unique information that affects house price change (for example, higher ICS may indicator higher intention to buy a house), and that contributes to the positive correlation.

The first explanation implies that although ICS and ΔZHVI may be highly correlated, the information in ICS may already be embedded in other economic variables (such as unemployment rate, IPI, etc). On the other hand, the second explanation implies that ICS affects ΔZHVI through a new channel, and even other economic variables are included in the model, ICS should still have some additional explanatory power. To study which one is the case, we move on to the regression model. By adding economic and financial variables as control variables, we are able to check the additional explanatory power of ICS.

Regression

The regression results are summarised in Table 4.3. The regression results show that $\sum_{i=1}^{T^*} \beta_i$ in Model 4.4.1 is 0.035 (obtained at $T^* = 5$), and it is significant at 5% level. According to the regression equation, when ICS increases by 10, ΔZHVI increases by 0.35. The influence is quite significant. Adj-R^2 of Models 4.4.1 and 4.4.2 are 0.609 and 0.378, respectively. By adding one explanatory variable ICS, adj-R^2 increases by 61%. . ICS alone is able to generate adj-R^2 of 0.487 (obtained at $T^* = 3$). These results imply that ICS alone can explain ΔZHVI quite well.Even taking other control variables into account, ICS has good additional explanatory power on ΔZHVI. The results indicate that the second explanation we discussed in the previous section is likely to hold. ICS is not just a reflection of fundamentals. They contain unique information that is extremely useful in explaining house price change.

Table 4.3
Influence of ICS on ΔZHVI from Regression Results

	With ICS only (3)			With Z only (2)	With ICS and Z (1)			Incremental [(1)-(2)]
	Adj-R^2	$\sum \beta_i$	p	Adj-R^2	Adj-R^2	$\sum \beta_i$	p	Adj-R^2
regression	0.487	0.026	0.00	0.378	0.609	0.035	0.00	0.231 (61%)

Note: Models (1) - (3) are as follows, respectively:
$\Delta \text{ZHVI}_t = \alpha + \sum_{i=1}^{T^*} \beta_i \text{ICS}_{t-i} + \gamma \text{Z}_{t-1} + \epsilon$
$\Delta \text{ZHVI}_t = \alpha + \gamma \text{Z}_{t-1} + \epsilon$
$\Delta \text{ZHVI}_t = \alpha + \sum_{i=1}^{T^*} \beta_i \text{ICS}_{t-i} + \epsilon$
Here, T^* is chosen by Akaike information criterion. $T^* = 5$ for Model (1), and $T^* = 3$ for model (3). $Z = \{\Delta\text{IPI}, \text{INF}, \Delta(\text{INT}), \text{UNE}\}$. Refer to Table 4.1 for variable notation.

VAR Model

The results from the VAR models are summarised in Table 4.4. The optimal numbers of lags according to Akaike information criterion is 2. Since lagged ΔZHVI values are added, R^2 is quite high for all the models, and the additional explanatory power by adding ICS is small. However, the results still confirm a positive relationship with ΔZHVI (i.e., positive $\sum \beta_i$ values) and a small additional explanatory power. The results are consistent with our expectations. In the next few subsections, we interpret the VAR model by three approaches, which can not be done in the regression model.

Table 4.4
Influence of ICS on ΔZHVI from VAR Results

	With ICS only			With Z only	With ICS and Z			Incremental
	Adj-R^2 (3)	$\sum \beta_i$	p	Adj-R^2 (2)	Adj-R^2 (1)	$\sum \beta_i$	p	Adj-R^2 [(1)-(2)]
VAR	0.956	0.0005	–	0.956	0.957	0.0027	–	0.001

Note: Refer to Table 4.1 for variable notation. Models (1) - (3) have the following form:
$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_{T^*} y_{t-T^*} + e_t$
For Model (1), $y = \{\Delta \text{ZHVI}, ICS, Z\}$, where Z is defined in Table 4.3.
For Model (2), $y = \{\Delta \text{ZHVI}, Z\}$. For Model (3), $y = \{\Delta \text{ZHVI}, ICS\}$.
Here, T^* is the optimal number of lags chosen by Akaike information criterion. $T^* = 2$ for model (1) and $T^* = 1$ for model (3).

Granger Causality

The Granger Causality results are summarised in Table 4.5. It shows that at test critical value 5%, for the complete model, ICS and ΔZHVI Granger cause each other. And for pairwise model, ICS Granger causes ΔZHVI, but ΔZHVI does not Granger cause ICS. This implies that the lagged values of ICSs have extra explanatory power on ΔZHVI given its own lagged values, but not the other way around. The result is consistent with our hypothesis. The change in ICS leads the change in house price changing rate.

There are a few explanations for this. On the one hand, ICS may imply the current business condition, which may cause change in housing market performance. On the other hand, as a psychological factor, ICS may change people's willingness to buy/sell a house, and influence housing market performance.

In contrast, change in ΔZHVI might also lead ICS. When the housing market becomes turbulent, people may become more pessimistic. This part is supported by the Granger Causality result for the complete model.

Table 4.5
Granger Causality Results

Panel A: Pairwise Granger Causality

Null Hypothesis:	F-Statistic	Prob.
ICS does not Granger Cause ΔZHVI	2.41	0.0096
ΔZHVI does not Granger Cause ICS	1.34	0.2075

Panel B: Granger Causality for the Complete VAR Model

Dependent Variable	Excluded	Chi-sq	Prob.
ΔZHVI	ICS	7.49	0.0236
ICS	ΔZHVI	6.48	0.0392

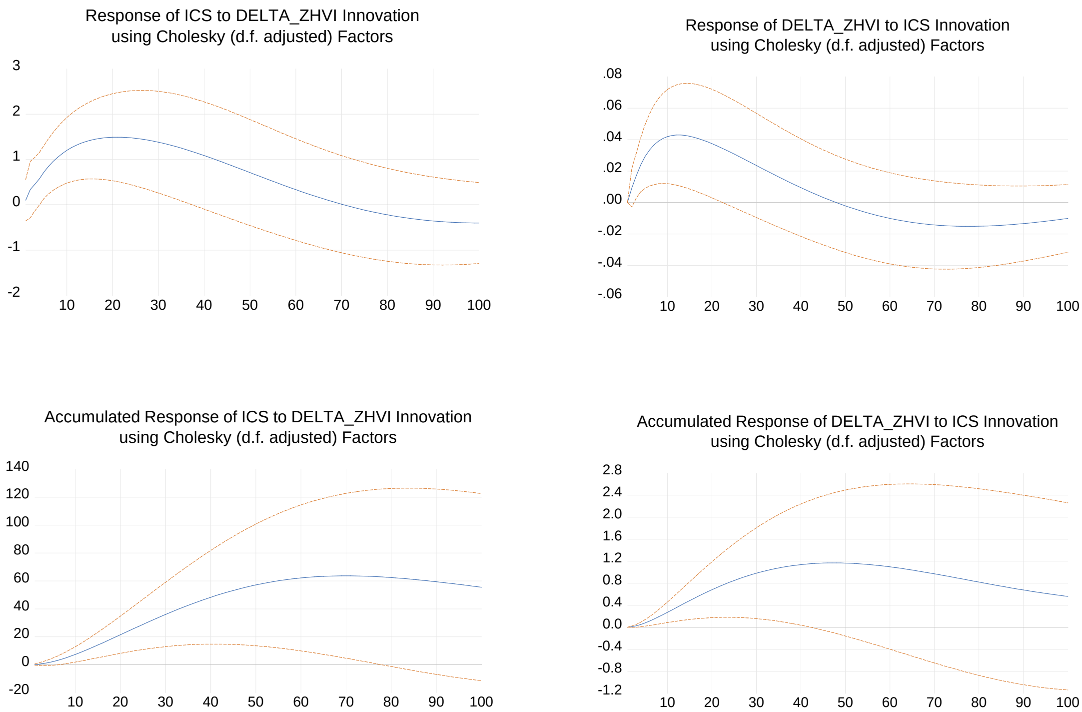
Note: Refer to Table 4.1 for variable notation. for Panel A, lag number 10 is used. For Panel B, optimal number of lags from model (1) is used.

Impulse Response Functions

Figure 4.10 shows the impulse responses between ICS and ΔZHVI. When there is a one standard-deviation shock in ΔZHVI, ICS has a positive response in a couple of months, and the shock is absorbed slowly. The biggest increase in ICS is around 1 point. By around 30 months, the influence is completely gone. Cumulatively, it has a positive impact for at least 5 years. On the other hand, when there is a shock in ICS, ΔZHVI has a positive response immediately, and the shock is absorbed slowly. The influence is gone in less than 20 months. The biggest increase in ΔZHVI is around 0.04. This number is quite big, considering it is the monthly percentage change in house price. Cumulatively, it has a positive impact in the short run and the impact is gone in 40 months. The results show that ICS and ΔZHVI do have a positive relationship, and also, ΔZHVI seems to respond to the shock in ICS more quickly and more significantly. which are consistent with our hypothesis and the previous results.

The impact of shocks in the short run and the long run can be further analysed by variance decomposition, which is discussed in the next subsection.

Figure 4.10
Impulse Response Results



Note: optimal # of lags = 2.

Variance Decomposition

Table 4.6 shows the variance decomposition results. In the short run (i.e., at the second month), a shock in ICS explains about 0.45% of the variance in ΔZHVI, largest among all the variables except for ΔZHVI itself. In the long run (i.e., after 100 months), a shock in ICS explains about 19% of the variance in ΔZHVI. Meanwhile, ΔZHVI's own shock still accounts for 73% of its variance. This result indicates the amount of information ICS contributes to ΔZHVI in the autoregression is noticeable. It is consistent with our hypothesis.

In the table, we also list the variance decomposition results for ICS. Comparing the results for ICS and ΔZHVI. From these results, we can clearly see that comparing with the effects of the control variables, two main variables, ICS and ΔZHVI, are relatively important in affecting each other.

Table 4.6
Variance Decomposition Results

Panel A: Variance Decomposition Results for ΔZHVI

Period	S.E.	ΔZHVI	ICS	ΔIPI	INF	INT	UNE
1	0.10	100.00	0.00	0.00	0.00	0.00	0.00
2	0.14	99.46	0.45	0.03	0.01	0.02	0.03
3	0.17	98.58	1.31	0.03	0.01	0.06	0.02
...				......			
100	0.49	72.86	19.22	0.86	0.57	4.26	2.24

Panel B: Variance Decomposition Results for ICS

Period	S.E.	ΔZHVI	ICS	ΔIPI	INF	INT	UNE
1	0.10	0.07	91.52	0.12	1.51	4.44	2.34
2	0.14	0.48	87.89	0.53	3.84	4.73	2.52
3	0.17	0.96	85.90	1.28	4.34	4.64	2.89
...				......			
100	0.49	41.44	48.15	1.55	2.11	3.99	2.76

Note: Cholesky Ordering: ΔZHVI ICS ΔIPI INF INT UNE.

4.5.2 Comparing the Relationship within Subgroups

In this section, we redo the same analyses as the previous section, by replacing ICS with subgroup specific values, and by replacing ΔZHVI with the value within a certain price tier. The objective is to compare the relationship of ICS and ΔZHVI among people in different income tiers, age groups, and regions, and among houses within different price tiers. In other words, in this section, we check the validity of our Hypotheses 2(a), 2(b), 2(c) and 3.

In particular, for consumer sentiment index, in addition to the overall ICS, we can also obtain consumer sentiment indices within certain demographic subgroups. In our study, we make use of the following variables:

- ICS_{i1}: ICS of people with bottom tiered income;
- ICS_{i2}: ICS of people with middle tiered income;
- ICS_{i3}: ICS of people with top tiered income.
- ICS_{a1}: ICS of people with age 34 and below;
- ICS_{a2}: ICS of people with age 35 to 54;
- ICS_{a3}: ICS of people with age 55 and above.
- ICS_{r1}: ICS of people living in the Midwest region;
- ICS_{r2}: ICS of people living in the North East region;
- ICS_{r3}: ICS of people living in the South region;
- ICS_{r4}: ICS of people living in the West region.
- ΔZHVI_1: ΔZHVI for houses whose price are in the bottom tier on local market;
- ΔZHVI_3: ΔZHVI for houses whose price are in the top tier on local market.

Among ICS series within three income tiers, we have found that they have slightly different explanatory powers on house price change. In the VAR model, R^2 is 0.9592, 0.9611, 0.9597, for people aged 34 and below, aged 35-54, and aged 55 and above, respectively. Quite clearly, middle aged people's sentiment is the best at explaining house price change. This is consistent with Hypothesis 2(a). The results are intuitive. People in a very young age group are less likely to be potential home buyers. Hence, their sentiment may not affect house price as much as middle-aged people do. On the other hand, very old people are less likely to buy a new house as well, which also makes their sentiment less important than middle-aged people?s one in determining house price.

Among ICS series within three age subgroups, we have found that they also have slightly different explanatory powers on house price change. In the VAR model, R^2 is 0.9600, 0.9595, 0.9605, for people with bottom-tiered income, middle-tiered income, and top-tiered income, respectively. Marginally, people whose income are in the top tier have sentiment that is the best at explaining house price change. This is consistent with Hypothesis 2(b). Consumers with higher income are more likely to be potential home buyers, and they tend to be more knowledgeable on the financial market. Hence, their sentiment is likely to play a more important role in determining house price change.

Among ICS series within four regions, again, the explanatory powers on house price change are region specific. In the VAR model, R^2 is 0.9606, 0.9594, 0.9595 and 0.9593, for people living in the Midwest, Northeast, South and West regions, respectively. Marginally, sentiment of people who live in Midwest is the best at explaining house price change. This is consistent with Hypothesis 2(c). There are clearly regional differences in house price, income levels, population, etc. These and other factors can all contribute to the difference in the results.

Among ΔZHVI series within three price tiers, we have found that ICS can explain slightly different percentages of their variance. In the VAR model, R^2 is 0.956, 0.960, 0.968, for bottom-tiered houses, overall houses, and top-tiered houses, respectively. Apparently, ICS explains the top tier price change the best. This is consistent with Hypothesis 3. The possible explanation is that higher valued houses may be more of an "luxury item" and hence sentiment plays a larger role in its buying and selling.

Here, we only summarise the most important VAR results. The detailed analyses are included in the Online Appendix. From the thorough analyses, we find evidence that support our Hypotheses 2(a), 2(b), 2(c) and 3.

Table 4.7
Correlation Matrices

	ICS	ICS_{a1}	ICS_{a2}	ICS_{a3}	ICS_{i1}	ICS_{i2}	ICS_{i3}	ICS_{r1}	ICS_{r2}	ICS_{r3}	ICS_{r4}
ΔZHVI	0.698	0.684	0.695	0.661	0.646	0.684	0.699	0.667	0.646	0.690	0.694
$\Delta ZHVI_1$	0.714	0.701	0.713	0.683	0.654	0.703	0.717	0.682	0.666	0.704	0.707
$\Delta ZHVI_3$	0.632	0.631	0.628	0.584	0.582	0.617	0.638	0.596	0.584	0.628	0.633

Correlation

Table 4.7 presents the correlations of the two (sub-grouped) main variables. As expected, when we replace the overall index with the index within a certain subgroup, the correlations of the two main variables are still positive and significant.

However, there are also some differences among different subgroups. They allow us to make some interesting observations.

Firstly, we compare different columns. Among different age subgroups, the sentiment indices by the mid-aged subgroup almost always have the largest correlation with house price change. For the overall house price change, the correlation is 0.695, larger than the one for the younger group, 0.684, and the one for the older group, 0.661. For the bottom tiered house price change, the correlation is 0.713, larger than the one for the younger group, 0.714, and the one for the older group, 0.713. For the top tiered house price change, the correlation is 0.628, only slightly smaller than the one for the younger group, 0.631, and larger than the one for the older group, 0.584. On the other hand, the older people (over 55 years old)'s sentiment always has the smallest correlation with house price change.

The results are easy to interpret. The middle aged group (from 35 to 54 years old) is the main player in the housing market. The younger people (who are less than 34 years old) may not have earned and saved enough deposit to buy a house. And the older people (who are more than 55 years old) may have already bought a house and no longer interested in buying a new one, and may have been the least interested in the housing market. As a result, the middle aged people are more interested and more knowledgeable about the housing market and house price change. Therefore, their sentiment reflects house price change better. This result also implies that sentiment is not generated out of nowhere. It is not just instinct. It is actually generated based on people's knowledge, based on things such as the news they read, the events that recently take place, etc. When people pay more attention and invest more time, they have a better understanding on the issue, and hence their sentiment is more valuable in reflecting reality.

Similarly, among income subgroups, an observation that does not surprise us is that the sentiment of people with higher income has higher correlation with house price change. Specifically, the correlation between overall house price change and the sentiment of people in the top income tier is 0.699, higher than the one with middle-tiered income, 0.684, which is higher than the one for bottom-tiered income, 0.646. For top-tiered house price change, the correlations are 0.717, 0.703, 0.654, for people under top, middle and bottom income tiers, respectively. The correlations also show a decreasing trend. Same is true for the top-tiered house price change. The correlations are 0.638, 0.617 and 0.582, for people under top, middle and bottom income tiers, respectively.

This is consistent with our previous discussion - sentiment reflects people's knowledge. People with higher income tend to have more money to buy a house, and hence more interested and more knowledgeable in the housing market. Their views are more valuable in reflecting real house price change.

The results also show a regional difference. The correlations between sentiment and house price change always show a decreasing trend for sentiment of people in the West Region, South Region, Midwest Region, and North East region, respectively. No matter this is for over all price change, top-tiered price change or bottom-tiered price change.

Secondly, we compare the correlations of different rows. It seems that the values in the second row (for bottom-tiered price changes) are always larger than that in the first row (for over all price changes). And the values in the first row are always larger than the ones in the third row (for top-tiered price changes). This result implies that people's sentiment reflects house price change better, for lower priced houses. One possible explanation is that lower priced houses are more affordable. Therefore, larger number of people are interested and knowledgeable about their price trend. And in return, their sentiment reflects their price better. On the other hand, higher priced houses only interest a smaller pool of people. Therefore, their prices tend to be less predictable by general customers.

Regression

The regression results for all the subgroups are summarised in Table 4.8. Across different age groups, the extra explanatory power of sentiment on house price change is the biggest for the middle aged group, for overall house price change (at 0.229), bottom-tier price change (at 0.182), and top-tier price change (at 0.211). On the other hand, the extra explanatory power is the smallest for the oldest age group, , for overall house price change (at 0.172), bottom-tier price change (at 0.129), and top-tier price change (at 0.151). The results are similar to the correlation results in the previous section. It supports our hypothesis that the middle aged group (aged 35 to 54), as the main player in the housing market, have better knowledge about information on house price change, and hence their sentiment is the most useful in n explaining house price change for various price tiers. And the older group (aged 55 and above) tend to be less interested in the housing market, and their sentiment is less powerful in explaining house price change.

Across different income tiers, the extra explanatory power of sentiment on house price change is the bigger when the in

Across different price tiers, we can see that the control variables have higher explanatory power on the house price change for cheaper houses (the adjusted R^2 is 0.523, 0.378, and 0.256, for bottom-tier, overall, and top-tier price change, respectively). And the extra explanatory power of sentiment tends to be smaller for cheaper houses. In other words,

4.5.3 The Construction of IHCS

As explained in Methodology Section, we start with 13 candidate questions. Then Forward Stepwise Regression is performed with $p-$value $= 0.05$. The following variables have survived in the model: Q45, Q30, Q06, Q41, Q25, and Q28.

Therefore, our first candidate IHCS proxy is calculated as follows:

$$\text{IHCS}_1 = (\text{A6}+\text{A25}+\text{A28}+\text{A30}+\text{A41}+\text{A45})/6.$$

On the other hand, the second candidate from Cai et al. (2015) is:

Table 4.8
Influence of ICS on ΔZHVI from Regression Results

	With ICS only (3)			w/ Z only (2)	With ICS and Z (1)			Incremental [(1)-(2)]
	Adj-R^2	$\sum \beta_i$	p	Adj-R^2	Adj-R^2	$\sum \beta_i$	p	Adj-R^2
regression	0.487	0.026	0.00	0.378	0.609	0.035	0.00	0.231 (61%)
(ICS_{a1}, ΔZHVI)	0.482	0.029	0.00	0.378	0.582	0.032	0.00	0.204 (54%)
(ICS_{a2}, ΔZHVI)	0.498	0.026	0.00	0.378	0.607	0.033	0.00	0.229 (61%)
(ICS_{a3}, ΔZHVI)	0.450	0.027	0.00	0.378	0.550	0.031	0.00	0.172 (46%)
(ICS_{i1}, ΔZHVI)	0.453	0.029	0.00	0.378	0.557	0.031	0.00	0.179 (47%)
(ICS_{i2}, ΔZHVI)	0.477	0.024	0.00	0.378	0.599	0.032	0.00	0.221 (59%)
(ICS_{i3}, ΔZHVI)	0.487	0.024	0.00	0.378	0.615	0.033	0.00	0.237 (63%)
(ICS_{r1}, ΔZHVI)	0.469	0.026	0.00	0.378	0.575	0.029	0.00	0.197 (52%)
(ICS_{r2}, ΔZHVI)	0.438	0.025	0.00	0.378	0.538	0.026	0.00	0.160 (42%)
(ICS_{r3}, ΔZHVI)	0.476	0.025	0.00	0.378	0.595	0.034	0.00	0.217 (58%)
(ICS_{r4}, ΔZHVI)	0.496	0.026	0.00	0.378	0.658	0.040	0.00	0.280 (74%)
(ICS, ΔZHVI_1)	0.518	0.036	0.00	0.523	0.701	0.040	0.00	0.178 (34%)
(ICS_{a1}, ΔZHVI_1)	0.532	0.040	0.00	0.523	0.701	0.039	0.00	0.178 (34%)
(ICS_{a2}, ΔZHVI_1)	0.534	0.036	0.00	0.523	0.705	0.039	0.00	0.182 (35%)
(ICS_{a3}, ΔZHVI_1)	0.483	0.037	0.00	0.523	0.652	0.035	0.00	0.129 (25%)
(ICS_{i1}, ΔZHVI_1)	0.470	0.039	0.00	0.523	0.652	0.035	0.00	0.129 (25%)
(ICS_{i2}, ΔZHVI_1)	0.515	0.033	0.00	0.523	0.700	0.038	0.00	0.177 (34%)
(ICS_{i3}, ΔZHVI_1)	0.522	0.033	0.00	0.523	0.713	0.039	0.00	0.190 (36%)
(ICS_{r1}, ΔZHVI_1)	0.506	0.035	0.00	0.523	0.684	0.035	0.00	0.161 (31%)
(ICS_{r2}, ΔZHVI_1)	0.481	0.034	0.00	0.523	0.657	0.031	0.00	0.134 (26%)
(ICS_{r3}, ΔZHVI_1)	0.500	0.034	0.00	0.523	0.674	0.038	0.00	0.150 (29%)
(ICS_{r4}, ΔZHVI_1)	0.528	0.036	0.00	0.523	0.752	0.047	0.00	0.229 (44%)
(ICS, ΔZHVI_3)	0.398	0.023	0.00	0.256	0.477	0.034	0.00	0.221 (86%)
(ICS_{a1}, ΔZHVI_3)	0.405	0.026	0.00	0.256	0.463	0.032	0.00	0.207 (81%)
(ICS_{a2}, ΔZHVI_3)	0.401	0.023	0.00	0.256	0.467	0.032	0.00	0.211 (82%)
(ICS_{a3}, ΔZHVI_3)	0.353	0.024	0.00	0.256	0.407	0.030	0.00	0.151 (59%)
(ICS_{i1}, ΔZHVI_3)	0.369	0.026	0.00	0.256	0.428	0.030	0.00	0.172 (67%)
(ICS_{i2}, ΔZHVI_3)	0.386	0.021	0.00	0.256	0.464	0.031	0.00	0.208 (81%)
(ICS_{i3}, ΔZHVI_3)	0.402	0.021	0.00	0.256	0.488	0.033	0.00	0.232 (91%)
(ICS_{r1}, ΔZHVI_3)	0.373	0.023	0.00	0.256	0.431	0.028	0.00	0.175 (68%)
(ICS_{r2}, ΔZHVI_3)	0.358	0.022	0.00	0.256	0.409	0.025	0.00	0.153 (60%)
(ICS_{r3}, ΔZHVI_3)	0.392	0.022	0.00	0.256	0.477	0.035	0.00	0.221 (86%)
(ICS_{r4}, ΔZHVI_3)	0.410	0.024	0.00	0.256	0.527	0.039	0.00	0.271 (106%)

Note: Models (1) - (3) are as follows, respectively:
$\Delta\text{ZHVI}_t = \alpha + \sum_{i=1}^{T^*} \beta_i \text{ICS}_{t-i} + \gamma \text{Z}_{t-1} + \epsilon$
$\Delta\text{ZHVI}_t = \alpha + \gamma \text{Z}_{t-1} + \epsilon$
$\Delta\text{ZHVI}_t = \alpha + \sum_{i=1}^{T^*} \beta_i \text{ICS}_{t-i} + \epsilon$
Here, T^* is chosen by Akaike information criterion. $T^* = 3$ for both model (1) and model (3).
$Z = \{\Delta\text{IPI}, \text{INF}, \Delta(\text{INT}), \text{UNE}\}$. Refer to Table 4.1 for variable notation.

$\text{IHCS}_2 = (\text{A6}+\text{A30}+\text{A31}+\text{A41}+\text{A43})/5.$

We consider the simple regression model $\Delta\text{ZHVI} = \alpha X + \beta$, where X is ICS, IHCS_1 , or IHCS_2 . The resulting R^2 is 0.49, 0.60, or 0.64, respectively. The values 0.6 and 0.64 are much bigger than 0.49. This implies that both constructed indices IHCS_1 and IHCS_2 explain a significantly larger part of the variance in ΔZHVI than the original ICS does. Within these two constructed indices, IHCS_2 performs slightly better than IHCS_1 (as 0.64 is slightly larger than 0.60).

Finally, we perform pairwise Granger Causality Test on these three variables and ΔZHVI. The results are listed in Table 4.9. The results are quite interesting. At p-value = 0.10, ICS, IHCS_1 and IHCS_2 all Granger causes ΔZHVI, but ΔZHVI only Granger causes IHCS_1. Within the three sentiment measures, both IHCS_1 and IHCS_2 Granger cause ICS, but not the other way around. And finally, IHCS_2 Granger causes IHCS_1, but not the other way around. The results imply that IHCS_2 seems to be leading variable that change before other variables do.

Based on the regression and pairwise Granger Causality Test results. we decide to use IHCS_2 as our housing specific consumer sentiment index, i.e.,

$\text{IHCS} = (\text{A6}+\text{A30}+\text{A31}+\text{A41}+\text{A43})/5.$

Questions 6, 30, 31, 41, and 43 are on the following issues, respectively: current personal financial condition, unemployment rate prediction, interest rate prediction, whether it is a good time to buy a house, and whether it is a good time to sell a house. Clearly, the last two questions are directly related to house price, and not surprisingly included in the model. Current personal financial condition implies the money that is available, which is also directly linked with house purchase. Moreover, unemployment rate prediction implies future income prediction, and interest rate prediction is related to mortgage interest rate, and also the state of the economy. In summary, the housing specific consumer sentiment index we constructed combined information about consumers' current financial situation, future financial situation prediction, mortgage rate, and their direct opinions about current housing market. It combines current condition and future expectations, and is more housing specific, and hence could be better in predicting house price.

The time series of IHCS is plotted on Figure 4.11. From the figure, we can see

Table 4.9
Pairwise Granger Causality

Null Hypothesis:	F-Statistic	Prob.
ICS does not Granger Cause ΔZHVI	2.40698	0.0096
ΔZHVI does not Granger Cause ICS	1.3441	0.2075
$IHCS_1$ does not Granger Cause ΔZHVI	2.98785	0.0014
ΔZHVI does not Granger Cause $IHCS_1$	1.69508	0.0824
$IHCS_2$ does not Granger Cause ΔZHVI	1.80991	0.0594
ΔZHVI does not Granger Cause $IHCS_2$	1.16302	0.3165
$IHCS_1$ does not Granger Cause ICS	2.24039	0.0162
ICS does not Granger Cause $IHCS_1$	1.04051	0.4099
$IHCS_2$ does not Granger Cause ICS	1.86014	0.0514
ICS does not Granger Cause $IHCS_2$	0.49188	0.8945
$IHCS_2$ does not Granger Cause $IHCS_1$	1.73368	0.0739
$IHCS_1$ does not Granger Cause $IHCS_2$	0.54504	0.857

that the housing specific consumer sentiment that we constructed has share a similar trend with ICS, but also has some differences, especially in some time periods, such as from year 2012, and between 2002 and 2006. Interestingly, ΔZHVI also share the same trend during these time periods. This is especially true for the period between 2012 and 2014 when ΔZHVI diverts from ICS. However, from 2016 to 2019, ΔZHVI diverts from IHCS and follows a similar trend as ICS. Nonetheless, it is worth studying the explanatory power of IHCS on ΔZHVI, and compare it with the previous results for ICS.

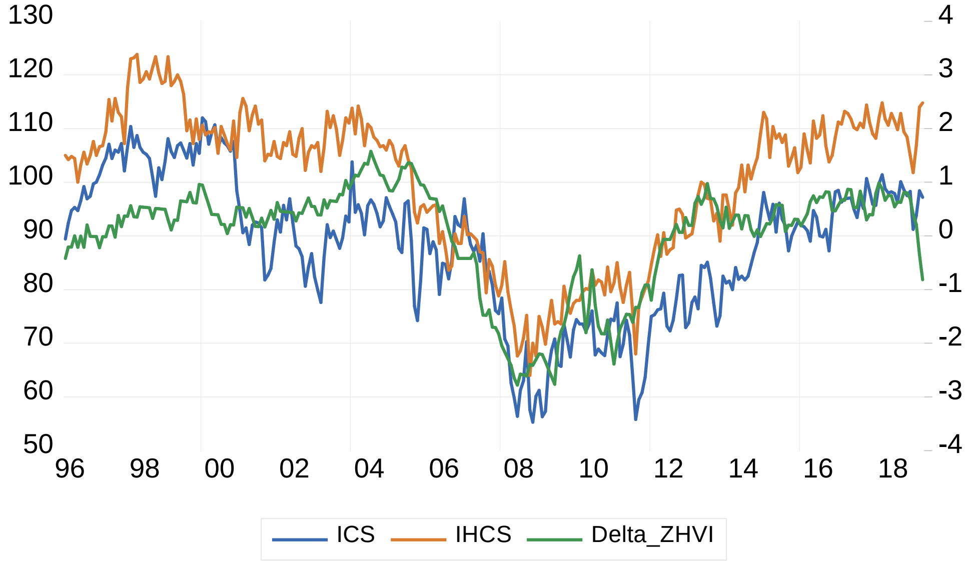
We redo the VAR analysis by replacing ICS with IHCS. We find $R^2 = 0.960$, which is very similar to the previous results for ICS. This indicates IHCS has very similar explanatory power to ICS. The result reconfirms that ICS already works pretty well in explaining house price changes.

We also find that IHCS granger causes ICS, and several ICS subgroup variables, but not the other way around. The results implies that IHCS works marginally better and seems to have a more leading role. Therefore, it is still worth using IHCS as the sentiment proxy.

4.5.4 The Construction of IHS

The first component from Principal Component Analysis result is as follows:

Figure 4.11
Time Series for IHCS, ICS and ΔZHVI from May 1996



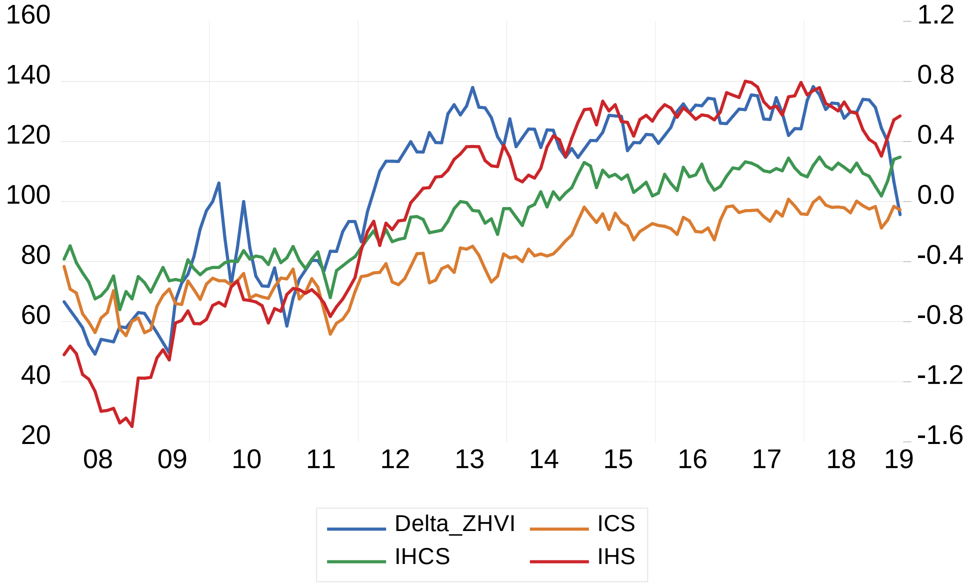
$$\text{IHS} = 0.53 \text{ IHCS} + 0.44 \text{ ILS} + 0.50 \text{ IRS} + 0.52 \text{ IBS}.$$

The consumer sentiment, lender sentiment, realtor sentiment and builder sentiment happen to have similar weights, indicating that the four variables are all important in providing unique information.

We redo the VAR analysis by replacing ICS with IHS. We find R^2 increases from 0.96 to 0.97. The result implies that by combining sentiment from four sources (demand side, supply side, intermediary agent and credit suppliers), the composite sentiment works much better than consumer confidence alone in explaining house price changes. We also found that IHS Granger causes IBS, and IRS Granger causes IHS. However, due to the shorter time range, the causality results are not very reliable.

We plot IHS, IHCS, ICS and ΔZHVI together on Figure 4.12. We can observe that there is a very high correlation between ΔZHVI and IHS, especially for the last five years of data. The advantage of IHS in explaining ΔZHVI is clearly demonstrated by the graph. However, since IRS is only available since 2008, our composite sentiment index is also available since 2008. It is hard to know whether or not our constructed sentiment index always works well in explaining ΔZHVI.

Figure 4.12
Time Series for IHS, IHCS, ICS and ΔZHVI from Jan 2008



4.6 Future Research

In the future, we are planning to do robustness study for sentiment and house price measures, and we can also study the role of EPU on house price. These results will further support our findings in this chapter.

4.6.1 Robustness Test

Robustness on Consumer Sentiment Measure

We can replace ICS by Conference Board's Consumer Confidence Index (CCI), and redo the analyses discussed in Basic Model section. We expect to find that the results are very similar and completely consistent. This will imply that our results are not restricted to one particular consumer sentiment measure. It can represent general consumer sentiment.

Robustness on House Price Measure

We may replace ZHVI by S&P/Case-Shiller U.S. National Home Price Index, and also redo the analyses discussed in Basic Model section. We expect to find that the results are very similar and completely consistent, as well. This will reply that our results are not restricted to one particular house price measure. It can represent general house price change.

4.6.2 The Role of Economic Policy Uncertainty (EPU)

in Chapter 1, we found that EPU was a determinant of ICS. However, intuitively, ICS is more directly linked with house price than EPU. So we may study whether EPU has extra explanatory power or not, when ICS is already included in the model. The results should show that EPU does not have much extra explanatory power. Hence, our model in the previous sections is good enough. We expect that the part of sentiment that is not related to economic policy uncertainty affects house price.

4.7 Conclusions

In Chapter 3, we used a VAR model to study the dynamics of consumer sentiment and house price. We focused on the role of sentiment on house price change, when economic factors are controlled for. We found that consumer sentiment is very powerful in explaining the percentage change in house price. It has big extra explanatory power on house price change, even when unemployment rate, interest rate, inflation rate and GDP change are all included in the model. We also found that consumer sentiment Granger causes house price change, which makes it a leading variable that might be very useful in predicting future house price change rate.

We went a step further by studying and comparing consumer sentiment within different income tiers, age groups, and regions. We found that the sentiment by mid-aged people, people with higher income, and people who live in Midwest, has the biggest explanatory power on house price change. it seemed that the sentiment of people with better knowledge and experience in housing market was more valuable in predicting house price change. This lead us to wonder: in addition to consumer sentiment, by adding sentiment by professionals who work in the housing market, we might be able to find a better sentiment proxy that could have better explanatory power on house price change.

Therefore, we proposed a two-step approach to achieve this goal. The first step was to construct a better consumer sentiment index, that is housing specific. We looked into the survey questions by University of Michigan's Survey of Consumers, and started with the questions that better represent peoples' sentiment on housing market. We then did a Stepwise Regression to select the set of variables that were able to explain the most variance on house price. Afterwards, we finalised our choice of questions by Stepwise Granger Causality test results. We used the responses of these questions to construct a housing specific consumer sentiment.

Our second step is to construct a sentiment of people who are the centre in the housing market. What kind of people are more related to the housing market? Consumers are one of them. They are potential house buyers. On the other side, builders are also important players. They influence the supplies of houses. And apparently, realtors, who work as intermediary between consumers and builders, have a central position on the housing market as well. Finally, the lenders who handle mortgage applications influence the buying and selling of houses indirectly but significantly. Hence, we aim at providing a sentiment measure that combines consumer sentiment (using the housing specific one we constructed), builder sentiment, realtor sentiment, and lender sentiment. Principal Component Analysis was used for the construction of the sentiment measure. And the measure turned out to be very successful in explaining house price change, compared with other sentiment measures.

In summary, we provide a thorough study on the role of sentiment on house price change and had some interesting results. Our findings should be valuable for both researchers and practitioners.

Chapter 5

Conclusions

In this thesis, we focused on monthly consumer sentiment (or confidence) index (ICS), and studied its determinants, interactions, and implications. Chapter 1 provided an Introduction to the problems we focused on. And the next three chapters focused on each of the three problems, determinants, interactions, and implications, respectively.

In Chapter 2, we provided empirical evidence on the role economic policy uncertainty (EPU) plays on consumer confidence through thorough data analyses. We not only studied the impact of economic policy uncertainty on consumer confidence without or with the presence of major economic variables, but also their dynamics through VAR models. We showed that higher economic policy uncertainty leads to lower consumer confidence, even when the other economic variables are controlled for. We also found that the EPU for US can explain consumer confidence better than Europe, but the additional explanatory power of EPU on ICS is actually smaller for the US than for Europe, adding the control variables. Moreover, we did four additional tests to further examine the relationship between economic policy uncertainty and consumer confidence. The additional tests were also useful in showing that (1) uncertainty implies lower confidence (through the analysis on "unsure" answers) and (2) confidence measures income expectation (through the analyses on categorised EPUs).

From all the results, we suggested that economic policy uncertainty affects consumer confidence through two channels. The first channel is that economic policy uncertainty implies current business conditions, and current business conditions affect consumers' income expectations, and therefore affect consumer confidence. On the other hand, the second channel is that economic policy uncertainty causes consumers' uncertainty about their income expectations, and hence affect consumer confidence.

We found that for the US, economic policy uncertainty mainly affects consumer confidence through the first channel. Therefore, its additional explanatory power is small. However, we also found evidence on the existence of the second channel. For example, economic policy uncertainty Granger causes other variables, and it explains the expected component of consumer confidence better. On the contrary, we found that for Europe, economic policy uncertainty mainly affects consumer confidence through the second channel. It has very large additional explanatory power on consumer confidence, compared with other economic variables.

However, unlike the US, economic policy uncertainty together with economic variables only explain a smaller portion of the variance in European consumer confidence. From the results, and the shapes of the consumer confidence times series for the US and Europe, we suspect that the consumer confidence in Europe may also be influenced by US confidence or variables. In the next chapter, we will study the transactions/spillover effects of consumer confidence across different regions.

In Chapter 3, we studied the transmission of consumer confidence around the globe. In particular, we focused on the G6 countries, and studied two problems: the directional spillover of consumer confidence, and the total spillover. The former focused on the "direction" of the relationship. We were able to identify each country's role - who are the receivers, and who are the contributors, and why. We found that US has by far the largest influence on the spillover of consumer confidence. This is not surprising, given it being the largest economy in the world. We have found that European countries, due to the close economic and geographic relationships, also influence each other frequently. But each country's role is time dependent, and is worth further study.

The second problem focused on the "magnitude" of the relationship, and its applications. We found that spillover is the highest at the beginning of a financial crises. Therefore, it has some predictory power on economic activities and economic turning points. This is because a large drop in consumer confidence in one country often leads large drops in consumer confidence in other countries, which in turn is a warning sign to world economy.

In this chapter, our research was motivated by theories and findings in the area of social psychology. Our research findings verified these findings, and hence provided some proof on what consumer confidence measures - consumer attitude.

In Chapter 4, we moved from what influences ICS, to what ICS influences. we used a VAR model to study the dynamics of consumer sentiment and house price. We focused on the role of sentiment on house price change, when economic factors are controlled for. We found that consumer sentiment is very powerful in explaining the percentage change in house price. It has big extra explanatory power on house price change, even when unemployment rate, interest rate, inflation rate and GDP change are all included in the model. We also found that consumer sentiment Granger causes house price change, which makes it a leading variable that might be very useful in predicting future house price change rate.

We went a step further by studying and comparing consumer sentiment within different income tiers, age groups, and regions. We found that the sentiment by mid-aged people, people with higher income, and people who live in Midwest, has the biggest explanatory power on house price change. it seemed that the sentiment of people with better knowledge and experience in housing market was more valuable in predicting house price change. This lead us to wonder: in addition to consumer sentiment, by adding sentiment by professionals who work in the housing market, we might be able to find a better sentiment proxy that could have better explanatory power on house price change.

Therefore, we proposed a two-step approach to achieve this goal. The first step was to construct a better consumer sentiment index, that is housing specific. We looked into the survey questions by University of Michigan's Survey of Consumers, and started with the questions that better represent peoples' sentiment on housing market. We then did a Stepwise Regression to select the set of variables that were able to explain the most variance on house price. Afterwards, we finalised our choice of questions by Stepwise Granger Causality test results. We used the responses of these questions to construct a housing specific consumer sentiment.

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Our research was closely linked with existing literature, such as Chau and Deesomsak (2014); Diebold and Yilmaz (2012); Ludvigson (2004); Ling et al. (2015). Nonetheless, we proposed many innovative approaches to studying consumer sentiment thoroughly, and and provided some interesting insights and interpretations on the variable. Our findings should be valuable for both researchers and practitioners.

Throughout the thesis, we have discussed several topics that we are interested in doing in our future research. Unfortunately they could not be done due to the time constraint and the scales of the problems. But we look forward to untangling them in the near future.

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Appendix A

Introduction to Consumer Confidence Indexes

Consumer confidence indexes are used to measure consumer confidence. Here, we give a detailed explanation on its constructions and comparisons.

A.1 Construction of the Three Major Indexes

Here we list three major indexes that aim to capture consumer confidence information. The information was gathered from their official sites.

- The US Consumer Sentiment Index (ICS)

  The Index of Consumer Sentiment (ICS) by the Survey Research Centre at University of Michigan is the first index of its kind, and is most widely studied in research papers. It was first introduced in 1946 and provided annually. It became quarterly available from 1952 to 1977, and monthly available since 1978.

  The index has been generated each month based on at least 500 consumers' phone responses to questions about current and expected personal/overall economic conditions.

  Fifty core questions are asked in the phone interview. But only five are used to calculate ICS. The questions are listed as follows:

- Q1 (current buying condition) Do you think now is a good or bad time for people to buy major household items?
- Q2 (current personal finance) Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?
- Q3 (expected business condition) do you think that during the next twelve months, well have good times financially or bad times or what?
- Q4 (expected long-term business condition) which would you say is more likelythat in the country as a whole well have continuous good times during the next five years or so or that well have periods of widespread unemployment or depression, or what?
- Q5 (expected personal finance) do you think that a year from now, you (and your family living there) will be better off financially, or worse off, or just about the same as now?

- The US Conference Board's Consumer Confidence Index (CCI)

  The Conference Board issues the monthly US Consumer Confidence Index (CCI) since 1967 based on mailed survey responses, and also received some research attention. The approximate sample size is 3500, while the exact number of responses is unknown. Since 1977, it moved from quarterly data to monthly ones.

  It is also calculated from the answers to five core questions. Here is a summary of the five questions:

  - Q1 (current business condition) How would you rate present general business conditions in your area?
  - Q2 (current employment condition) What would you say about available jobs in your area right now?
  - Q3 (expected business condition) Six months from now, do you think business conditions in your area will be?

- Q4 (expected employment condition) Six months from now, do you think there will be [more/same/fewer] jobs available in your area?
- Q5 (expected personal finance) How would you guess your total family income to be six months from now?

- The UK Consumer Confidence Barometer (CCB)

  The UK Consumer Confidence Barometer is conducted by GfK on behalf of the EU. This survey has been conducted via a nationally representative online survey, amongst a sample of 2000 individuals. It has been running since 1974, and monthly data have been provided. Similar surveys are conducted in each European country.

  The five questions of the CCB survey are as follows:

  - Q1 (current buying condition) In view of the general economic situation, do you think now is the right time for people to make major purchases such as furniture or electrical goods?

    Q2 (current business condition) How do you think the general economic situation in this country has changed over the last 12 months?
  - Q3 (current personal finance) How has the financial situation of your household changed over the last 12 months?
  - Q4 (expected business condition) How do you expect the general economic situation in this country to develop over the next 12 months?
  - Q5 (expected personal finance) How do you expect the financial position of your household to change over the next 12 months?

A.2 Comparison of the Three Major Indexes

Clearly, there are similarities and differences among the construction of the three indexes. Their major similarities are summarised below:

- The goal is to measure public confidence in the economy;

- The index is calculated based on the answers to five questions (as part of a larger survey);
- Each question is given equal weight;
- The questions can be categorised to two components: current condition component, and an expectation component;
- They all ask questions about (1) the current personal finance condition, (2) the expected personal finance condition, and (3) the expected business condition.

Their main differences are summarised as follows:

- For ICS and CCI, two questions are used to assess the current condition; while for CCB, three are used;
- For ICS and CCB, the current buying plan is asked directly; while for CCB, no such question is asked;
- For CCB, the current and expected employment condition are asked directly; while for the other two, no such questions are asked;
- For ICS, two questions about the expected business condition are asked, one for the short-term and one for the long-term; while the other two only ask one short-term question;
- They have different sample sizes and survey formats.

Due to the similarities, these indexes should be highly correlated. On the other hand, the question designs are distinct. For example, CCB puts more weight to current conditions, CCI is more closely tied to labour market conditions, and ICS focuses more on economic condition overlook. This may lead to systematical difference in responses. It could be an interesting question in our study to compare the performance of the different indexes.

Appendix B

The Conference Board Leading Economic Index

The Conference Board Leading Economic Index is an American economic leading indicator intended to forecast future economic activity. It is calculated by The Conference Board, a non-governmental organization, which determines the value of the index from the values of ten key variables. These variables have historically turned downward before a recession and upward before an expansion. The single index value composed from these ten variables has generally proved capable of predicting recessions over the past 50 years, but in most cases it has been known to falsely predict recessions which did not occur.

- *Average weekly hours (manufacturing)* - Adjustments to the working hours of existing employees are usually made in advance of new hires or layoffs, which is why the measure of average weekly hours is a leading indicator for changes in unemployment.

- *Average weekly jobless claims for unemployment insurance* - The CB reverses the value of this component from positive to negative because a positive reading indicates a loss in jobs. The initial jobless-claims data is more sensitive to business conditions than other measures of unemployment, and as such leads the monthly unemployment data released by the Department of Labor.

- *Manufacturer's new orders for consumer goods/materials* - This component is considered a leading indicator because increases in new orders for consumer goods and materials usually mean positive changes in actual production. The new orders decrease inventory and contribute to unfilled orders, a precursor to future revenue.

- *Vendor performance (slower deliveries diffusion index)* - This component measures the time it takes to deliver orders to industrial companies. Vendor performance leads the business cycle because an increase in delivery time can indicate rising demand for manufacturing supplies. Vendor performance is measured by a monthly survey from the National Association of Purchasing Managers (NAPM). This diffusion index measures one-half of the respondents reporting no change and all respondents reporting slower deliveries.

- *Manufacturer's new orders for non-defense capital goods* - As stated above, new orders lead the business cycle because increases in orders usually mean positive changes in actual production and perhaps rising demand. This measure is the producer's counterpart of new orders for consumer goods/materials component.

- *Building permits for new private housing units* - Building permits mean future construction, and construction moves ahead of other types of production, making this a leading indicator.

- *The Standard & Poor's 500 stock index* - The S&P 500 is considered a leading indicator because changes in stock prices reflect investor's expectations for the future of the economy and interest rates. The S&P 500 is a good measure of stock price as it incorporates the 500 largest companies in the United States.

- *Money Supply (M2)* - The money supply measures demand deposits, traveler's checks, savings deposits, currency, money market accounts and small-denomination time deposits. Here, M2 is adjusted for inflation by means of the deflator published by the federal government in the GDP report. Bank lending, a factor contributing to account deposits, usually declines when inflation increases faster than the money supply, which can make economic expansion more difficult. Thus, an increase in demand deposits will indicate expectations that inflation will rise, resulting in a decrease in bank lending and an increase in savings.

- *Interest rate spread (10-year Treasury vs. Federal Funds target)* - The interest rate spread is often referred to as the yield curve and implies the expected direction of short-, medium- and long-term interest rates. Changes in the yield curve have been the most accurate predictors of downturns in the economic cycle. This is particularly true when the curve becomes inverted, that is, when the longer-term returns are expected to be less than the short rates.

- *Index of consumer expectations* - This is the only component of the leading indicators that is based solely on expectations. This component leads the business cycle because consumer expectations can indicate future consumer spending or tightening. The data for this component comes from the University of Michigan's Survey Research Center, and is released once a month.

The information is obtained from Investopedia.